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A Brief Review of Nature-Inspired Computing Based Algorithms And Their Applications

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Abstract

Real world problems are hard and computationally incentive. Nature based solutions can be a great source of inspiration for optimizing challenging problems. Researchers are putting in lot of efforts to study and mimic the nature for finding optimal or near optimal solution of a problem.Nature inspired algorithms (NIC) can be broadly classified into evolutionary or swarm based algorithms based on the source of inspiration. In this paper we will study some of nature inspired computing based algorithms like Ant Colony Optimization (ACO), Particle Swarm optimization (PSO), Honey Bee Optimization algorithm, Genetic algorithm (GA) along with their applications.

Keywords:- Nature inspired computing, Optimization, ACO, PSO, GA

1Introduction

Nature has inspired the researchers to propose algorithms for solving a wide range of complex computation and optimization problems. Leaning from nature how it handles complex problems for which traditional methods do not work effectively will help in developing the intelligent system. Nature always evolves and moves towards optimization, using the same concept solution of hard real-world problems can be analyzed. Nature has many properties like self organization flexibility, robustness, collective work are used to derive nature inspired algorithms. Different nature inspired optimization algorithms are classified as swarm intelligence and evolutionary

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algorithms are derived from nature and are being used by different applications. Researchers and scientists have come up with different applications of nature-inspired algorithms ranging from engineering design, business planning, water distribution etc with an aim of achieving optimization.Optimization means tuning input values for a given function so as tominimize or maximize the output [1]. The optimized solution can either be the best solution or the solution relatively close to the best solution. The objective of optimization is problem specific which can be minimizing cost, energy consumption or maximizing the profit of a business or maximizing the network bandwidth utilization. In this paper nature inspired algorithms are discussed along with their different applications in real life.

2. BRIEF REPRESENTATION OF SELECTED NATURE INSPIRED ALGORITHMS

a) Ant Colony Optimization (ACO)

ACO algorithm was proposed in early 1990's by M. Dorigo [2][3][4] which is based on the behavior of ants and a phenomenon known as stigmergy[94] (term introduced by French biologist in 1959 and means a mechanism of indirect co-ordination, though an environment, between agents and action) providing ants the ability to find the shortest path between ant's nest and food source by building path from pheromone[95] traces. Pheromone is a chemical substance laid down by the ant along their trail which decay over time. Path with most intensity of pheromones is the path which is followed by most ants. This indirect communication between ants enables them to find the optimum solution i.e. shortest path. Algorithm or pseudo code for ACO [5] is presented.

Algorithm 1

Begin

Generate Initialize population and pheromone matrix

fitness computation of initial population

While (stopping criterion not satisfied) **do**

Set position each ant as starting node

Repeat

For each ant **do**

Choose next node by applying the state transition rule

Apply step by step pheromone update

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End for

Until every a solution for every node is obtained

Evaluate fitness of population

Update best solution obtained

Apply Pheromone update

End While

End

Ant system can be considered as a graph where the pheromones update for edge E_{ij}joining nodesi and j is performed [6][7] as given below:

$$\mathrm{Eij} \leftarrow (1-\mathrm{p}).\mathrm{Eij} + \sum_{K=1}^{m} \Delta \mathrm{E}_{\mathrm{ij}}^{\mathrm{k}}$$

where p is the pheromone decay rate whose value is between (0,1), Total number of ants (m) and $\Delta \mathrm{E}_{\mathrm{ij}}^{\mathrm{k}}$ is the quality of pheromones laid by the kthant on the edge (i,j).

Transition probability $p\left(c_{ij}\middle|s_k^p\right)$of kth ant moving from node i to node j is given by:

$$p\left(c_{ij}\middle|s_k^p\right) = \begin{cases} \dfrac{E_{ij}^{\alpha} * \eta_{ij}^{\beta}}{\sum cij \in N\left(s_k^p\right) E_{ij}^{\alpha} * \eta_{ij}^{\beta}} & if\ j \in N\left(s_k^p\right), \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where η is an optional weighting function and $\eta = \frac{1}{d_{ij}}$, $d_{ij}$is the length of component c_{ij}, α and β are positive numbers and control the relative importance of pheromone and heuristic information.

b) PSO

PSOalgorithm was proposed in [98] and is an evolutionary computation techniquebased on research of the flock of birds[36] searching a food source[36]. PSO algorithm a birds groupis searching for food in an area where only one piece of food is available and birds don’t have the

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information about the exact location of the food source. Birds know the distance of food source from current location is. In this algorithm, all birds of the flock change their velocity based on their past experience and by following the bird nearest to the food. Each bird or solution in PSO is called particle[99]. Each particle's coordinates (possible solution in the search space) is represented by two vectors position $x_i$and velocity v_i. N-dimensional search space[100]of each particle can be represented by x_i=[xi1,xi2, xi3… xiN] and velocity vi=[vi1, vi2,vi3 … viN]. Searching the optimized solution in the search space is based on the particle's best position pbest and best position so far among the entire group of particles gbest. PSO optimization technique can be simply represented as:

$$v_i^{n+1} = v_i^n + c_1 r_1^n (pbest_i^n - x_i^n) + c_2 r_2 (gbest_i^n - x_i^n) \qquad (3)$$

$$x_i^{n+1} = x_i^n + v_i^{n+1} \qquad (4)$$

Where c_1 and c_2 are positive acceleration constants and r_1 and $r_2$are numbers in the range [0,1] and are random, $pbest_i^n$ is the best possible position of the particlei achieved in n iterations and $gbest_i^n$represents the most optimist position of the swarm in n iterations.

Changingthe velocity of particle consideringthe particle's best performance and the best performance by the closest particle the optimum solution is searched.

Algorithm or pseudo code for PSO [91] is presented below

Algorithm 2

Begin

For each particle

Initialize particle randomly

end for

Fori=1 **until** maximum iteration

Calculate every particle velocity (use equation 3)

Update every particle location (use equation 4)

For each particle **do**

calculate fitness for particle

if fitness better than the previouspbest then

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set fitness value as new pbest

end if

end for

Choose particle with the best pbest as gbest

End for

Return gbest

End

c) ABC Algorithm

ABC algorithm was presented by Karaboga in 2005 [63].In ABC algorithm communication about the direction, distance and quantity of nectar at food source is done by waggle dance by a honey bee. Bees are grouped into three categories employed foragers, unemployed foragers and experienced foragers [63, 64]. Bees that have no information about the food source are classified as unemployed. Unemployed foragers can either start searching for food source from a scratch without any prior knowledge and are called Scout Bee or can be a Recruit bee thatuses the information obtained by the waggle dance of another bee about the food source. Recruit bee after watching waggle dance of different bees decides about the most profitable food source. The recruited bee when finds the food source and starts extracting energy, it is classified and employed bee. Employed bee also shares information about the food source. Experienced bees use their prior knowledge for discovering new food source near their hives.

ABC algorithm uses exploration and exploitation for finding the best solution. After the food source is explored the bee memorizes the location and starts exploiting it. The bee loads the nectar from food source and unloads the nectar to a food store at their hive. Now the bee can abandon the food source, communicate with other bees about food source by waggle dance or keep forging the food source himself without any recruitment.

Algorithm or pseudo code for ABC [65] is presented below

Algorithm 3

Begin

Initialize the food source positions.

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Evaluate the food source

Fori=1 **until** maximum requirements meat

Produce the new food sources

Move the recruits to the food sources and determine the nactor

Apply greedy selection

Calculate the fitness and probability values

Memorize the best food source found so far i.egBest

End for

Return gBest

End

d) **GA**

Genetic Algorithm (GA) is a evolutionary method which was presented by "John Holland" in early 1960s [67]. GA is based on the natural evolution of a biological species and can be applied for stochastic search or for finding optimal or near-optimal solution. GA is inspired by the process of selection of a solution from a population based on (the theory of Darwin) a fitness function (maximization or minimization). Solution space comprising of Individuals also known as chromosomes matures with every generation so as to provide a optimal or near optimal solution. Individuals as selected based on a selection method (roulette wheel, Boltzmann selection, tournament selection, rank selection, steady stare selection etc) from population for reproduction. Cross-over method is applied for produce a new chromosome by combining parts of parents. Produced chromosome retains the useful features of the parents and ignores less useful features.

In order to avoid local optimality [68] some (low probability) of the offspring are mutated. Mutation causes genetic diversity by bringing a small change in the chromosome's element allele. Some the common mutation techniques are power mutation, uniform mutation, Gaussian mutation, shrink mutation etc. Chromosomes with the 'best fitness' value are retained

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in the new population. This process continues until the desired optimal solution is obtained or process continues for max number of generations.

Algorithm or pseudo code for GA [92,93] is presented below

Algorithm 4

Begin

Input population, cross-over probability, mutation probability

Initialize chromosomes randomly

W**hile** desired optimal solution or max generations are not reached **do**

update chromosomes by crossover and mutation operations

Compute the fitness of each chromosome

Save fitness values of chromosomes

Select chromosomes by using selection method for next generation

EndW**hile**

Report chromosome with best fitness value as an optimal solution

End

e) Other Algorithms

Researchers are continuously working on different new nature inspired algorithms to find and optimal solution.NIC algorithms can be classified into different classes like bio-inspired, swarm intelligence (SI) based, chemistry-based/physics and others Some of the well known algorithms are Cuckoo search optimization (CSO), Bat algorithm, Paddy Field Algorithm,flower pollination algorithm, Grey wolf optimizer (GWO), Glowworm Swarm Optimization, Firefly algorithm, Cat Swarm Optimization (CSO),Cuckoo search, Monkey search,Eagle strategy, Shuffled frog leaping algorithm, Big bang-big Crunch, Black hole,Gravitational searchetc [88]. Researchers are working on these algorithmsso as to increase their performance. For example "Parallel Big Bang–Big Crunch Global Optimization Algorithm" [89] was presented so as to increase the performance of Big bang-big crunch(B3C)[97]."Modified cuckoo search algorithm" with rough sets for feature selection was proposed so as to handle high dimensionality data[90].

3. Applications of few selected nature inspired algorithms

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Name of Algorithm	Representation	Operations	Applications	Control Parameters
ACO	Undirected Graph	Pheromone trail, update, evaporation, measure	Traveling Salesman Problem (TSP)[8,9],Text feature selection[10], Vehicle routing problem[11, 12], Face recognition [13], Cloud task scheduling [14], Training feed-forward neural networks [15], Structure-, based drug design [16], Protein folding problem[24],DNA sequencing[30],Data mining[17,18], Multi-purpose reservoir operation[19], Process planning[20],Graph coloring[21], Digital image processing [22, 23], Quadratic assignment[25,26,27], Supply chain management[28, 29], Multicasting ad-hoc networks [31,32,33],Project scheduling [34,35]	Total number of Ants, pheromone decay rate, iteration.
PSO	Dimensionality of vector for the position,speed,beststate and is Real-valued	Initializer, updater and evaluator.	Multimodal biomedical image registration[38], Iterated Prisoner‘s Dilemma[39], Classification of instances[40], Feature selection[41,42,43,44], web service selection[45], Power System Optimization problems [46,47], Edge detection in noisy images[48,49,50], Maximizing production[51], Scheduling problems[96] ,Vehicle routing problems[52], Artificial Neural Network[53,54,55],multi-objective,	Particles count, Dimension of particles, Range of particles, Learning factors:initialweight, themax number of iterations

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			Combinatorial optimization problems,QoS in adhoc multicast[56,57], Color image segmentation[58] , sequential ordering problem, constrained portfolio optimization problem, Signature verification[59], Optimization in Electric Power Systems[60,61], computational finance applications[62], convergence analysis and parameter selection[37]	
ABC	D dimensional vector	Recruitment of bee, searching new food source.	Numerical function Optimization[66], Optimizing feature selection[65], Colormap Quantization[69], feed-forward neural networks[70], set covering problem[71], distribution systems[72], real-parameter optimization[73], engineering design[74], examination timetabling problems[75,76], scheduling in grid environments[77], optimal power flow[78],traveling salesman problem[79], image edge enhancement[80], load balancing[81]	The maximum number of iterations, number of food sources, employed unemployed bee count

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Genetic Algorithm	Binary or real numbers	Selection Crossover Mutation	protein folding simulations[82,83],clustering and image segmentation[84],Data mining[85] graph and shape matching[86],genetic algorithms were used for registration of depth images, 2D shape recognition,rigid registration of 3-D curves and surfaces[87],	Population, Max generations, crossover and mutation probabilities, Chromosome length, chromosome encoding, and decoding

Conclusion

This paper provides an overview of different nature inspired algorithms. Some of the well known algorithms like ACO, PSO, ABC and GA are discussed in detail along with their representation, operations and applications. Other well known algorithms are also mentioned. NIC algorithms can be used for optimizing a solution of a complex and challenging problems. The scope of this field is very vast and there is lot of areas yet to be explored.

References:

1. Lhotska, L., Macaš, M., &Burša, M. (2006, September). PSO and ACO in Optimization Problems. In *International Conference on Intelligent Data Engineering and Automated Learning* (pp. 1390-1398). Springer, Berlin, Heidelberg.
2. Dorigo, M., Maniezzo, V., &Colorni, A. (1991). The ant system: An autocatalytic optimizing process.
3. Dorigo, M. (1992). Optimization, learning and natural algorithms. *PhD Thesis, Politecnico di Milano*.
4. Colorni, A., Dorigo, M., &Maniezzo, V. (1992, December). Distributed optimization by ant colonies. In *Proceedings of the first European conference on artificial life* (Vol. 142, pp. 134-142).
5. Reddy, M. J., & Kumar, D. N. (2012). Computational algorithms inspired by biological processes and evolution. *Current Science*, 370-380.
6. Kanan, H. R., &Faez, K. (2008). An improved feature selection method based on ant colony optimization (ACO) evaluated on face recognition system. *Applied Mathematics and Computation*, *205*(2), 716-725.
7. Pan, W., & Wang, L. (2009, August). An ant colony optimization algorithm based on the experience model. In *2009 Fifth International Conference on Natural Computation*(Vol. 3, pp. 13-18). IEEE.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

8. Brezina Jr, I., &Čičková, Z. (2011). Solving the travelling salesman problem using the ant colony optimization. *Management Information Systems*, *6*(4), 10-14.
9. Hingrajiya, K. H., Gupta, R. K., &Chandel, G. S. (2012). An ant colony optimization algorithm for solving travelling salesman problem. *International Journal of Scientific and Research Publications*, *2*(8), 1-6.
10. Aghdam, M. H., Ghasem-Aghaee, N., &Basiri, M. E. (2009). Text feature selection using ant colony optimization. *Expert systems with applications*, *36*(3), 6843-6853.
11. Dorigo, M. (1992). *Ant Colony Optimization for vehicle routing problem* (Doctoral dissertation, PhD thesis, Politecnico di Milano, Milan, Italy).
12. Yu, B., Yang, Z. Z., & Yao, B. (2009). An improved ant colony optimization for vehicle routing problem. *European journal of operational research*, *196*(1), 171-176.
13. Yan, Z., & Yuan, C. (2004, July). Ant colony optimization for feature selection in face recognition. In *International Conference on Biometric Authentication* (pp. 221-226). Springer, Berlin, Heidelberg.
14. Li, K., Xu, G., Zhao, G., Dong, Y., & Wang, D. (2011, August). Cloud task scheduling based on load balancing ant colony optimization. In *2011 Sixth Annual ChinaGrid Conference* (pp. 3-9). IEEE.
15. Socha, K., & Blum, C. (2007). An ant colony optimization algorithm for continuous optimization: application to feed-forward neural network training. *Neural Computing and Applications*, *16*(3), 235-247.
16. Korb, O., Stützle, T., & Exner, T. E. (2006, September). PLANTS: Application of ant colony optimization to structure-based drug design. In *International Workshop on Ant Colony Optimization and Swarm Intelligence* (pp. 247-258). Springer, Berlin, Heidelberg.
17. Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2002). Data mining with an ant colony optimization algorithm. *IEEE transactions on evolutionary computation*, *6*(4), 321-332.
18. Michelakos, I., Mallios, N., Papageorgiou, E., &Vassilakopoulos, M. (2011). Ant colony optimization and data mining. In *Next Generation Data Technologies for Collective Computational Intelligence* (pp. 31-60). Springer, Berlin, Heidelberg.
19. Kumar, D. N., & Reddy, M. J. (2006). Ant colony optimization for multi-purpose reservoir operation. *Water Resources Management*, *20*(6), 879-898.
20. Liu, X. J., Yi, H., & Ni, Z. H. (2013). Application of ant colony optimization algorithm in process planning optimization. *Journal of Intelligent Manufacturing*, *24*(1), 1-13.
21. Dowsland, K. A., & Thompson, J. M. (2008). An improved ant colony optimisation heuristic for graph colouring. *Discrete Applied Mathematics*, *156*(3), 313-324.
22. Lee, M. E., Kim, S. H., Cho, W. H., Park, S. Y., & Lim, J. S. (2009, June). Segmentation of brain MR images using an ant colony optimization algorithm. In *2009 Ninth IEEE International Conference on Bioinformatics and Bioengineering* (pp. 366-369). IEEE.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

23. Hoseini, P., &Shayesteh, M. G. (2013). Efficient contrast enhancement of images using hybrid ant colony optimisation, genetic algorithm, and simulated annealing. *Digital Signal Processing*, *23*(3), 879-893.

24. Shmygelska, A., &Hoos, H. H. (2003, June). An improved ant colony optimisation algorithm for the 2D HP protein folding problem. In *Conference of the Canadian Society for Computational Studies of Intelligence* (pp. 400-417). Springer, Berlin, Heidelberg.

25. Stützle, T., & Dorigo, M. (1999). ACO algorithms for the quadratic assignment problem. *New ideas in optimization*, (C50), 33.

26. López-Ibánez, M., Paquete, L., &Stützle, T. (2004, September). On the design of ACO for the biobjective quadratic assignment problem. In *International Workshop on Ant Colony Optimization and Swarm Intelligence* (pp. 214-225). Springer, Berlin, Heidelberg.

27. Demirel, N. Ç., &Toksarı, M. D. (2006). Optimization of the quadratic assignment problem using an ant colony algorithm. *Applied Mathematics and Computation*, *183*(1), 427-435.

28. Silva, C. A., Sousa, J. M. C., Runkler, T. A., & Da Costa, J. S. (2009). Distributed supply chain management using ant colony optimization. *European Journal of Operational Research*, *199*(2), 349-358.

29. Xu, S., Liu, Y., & Chen, M. (2017). Optimisation of partial collaborative transportation scheduling in supply chain management with 3PL using ACO. *Expert Systems with Applications*, *71*, 173-191.

30. Blum, C., Vallès, M. Y., &Blesa, M. J. (2008). An ant colony optimization algorithm for DNA sequencing by hybridization. *Computers & Operations Research*, *35*(11), 3620-3635.

31. Souza, A. B., Celestino, J., Xavier, F. A., Oliveira, F. D., Patel, A., &Latifi, M. (2013, January). Stable multicast trees based on Ant Colony optimization for vehicular Ad Hoc networks. In *The International Conference on Information Networking 2013 (ICOIN)* (pp. 101-106). IEEE.

32. Hernández, H., & Blum, C. (2009). Ant colony optimization for multicasting in static wireless ad-hoc networks. *Swarm Intelligence*, *3*(2), 125-148.

33. Hernández, H., Blum, C., &Francès, G. (2008, September). Ant colony optimization for energy-efficient broadcasting in ad-hoc networks. In *International Conference on Ant Colony Optimization and Swarm Intelligence* (pp. 25-36). Springer, Berlin, Heidelberg.

34. Chen, W., Shi, Y. J., Teng, H. F., Lan, X. P., & Hu, L. C. (2010). An efficient hybrid algorithm for resource-constrained project scheduling. *Information Sciences*, *180*(6), 1031-1039.

35. Tseng, L. Y., & Chen, S. C. (2006). A hybrid metaheuristic for the resource-constrained project scheduling problem. *European Journal of Operational Research*, *175*(2), 707-721.

36. Wang, D., Tan, D., & Liu, L. (2018). Particle swarm optimization algorithm: an overview. *Soft Computing*, *22*(2), 387-408.

37. Trelea, I. C. (2003). The particle swarm optimization algorithm: convergence analysis and parameter selection. *Information processing letters*, *85*(6), 317-325.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

38. Wachowiak, M. P., Smolíková, R., Zheng, Y., Zurada, J. M., &Elmaghraby, A. S. (2004). An approach to multimodal biomedical image registration utilizing particle swarm optimization. *IEEE Transactions on evolutionary computation*, *8*(3), 289-301.
39. Franken, N., & Engelbrecht, A. P. (2005). Particle swarm optimization approaches to coevolve strategies for the iterated prisoner's dilemma. *IEEE Transactions on evolutionary computation*, *9*(6), 562-579.
40. De Falco, I., Della Cioppa, A., & Tarantino, E. (2005, September). Evaluation of particle swarm optimization effectiveness in classification. In *International Workshop on Fuzzy Logic and Applications* (pp. 164-171). Springer, Berlin, Heidelberg.
41. Trelea, I. C. (2003). The particle swarm optimization algorithm: convergence analysis and parameter selection. *Information processing letters*, *85*(6), 317-325.
42. Ghamisi, P., &Benediktsson, J. A. (2015). Feature selection based on hybridization of genetic algorithm and particle swarm optimization. *IEEE Geoscience and remote sensing letters*, *12*(2), 309-313.
43. Liu, Y., Wang, G., Chen, H., Dong, H., Zhu, X., & Wang, S. (2011). An improved particle swarm optimization for feature selection. *Journal of Bionic Engineering*, *8*(2), 191-200.
44. Babaoglu, İ., Findik, O., &Ülker, E. (2010). A comparison of feature selection models utilizing binary particle swarm optimization and genetic algorithm in determining coronary artery disease using support vector machine. *Expert Systems with Applications*, *37*(4), 3177-3183.
45. Zhang, T. (2014). QoS-aware web service selection based on particle swarm optimization. *Journal of Networks*, *9*(3), 565-571.
46. Abido, M. A. (2002). Optimal power flow using particle swarm optimization. *International Journal of Electrical Power & Energy Systems*, *24*(7), 563-571.
47. Abido, M. A. (2002). Optimal design of power-system stabilizers using particle swarm optimization. *IEEE transactions on energy conversion*, *17*(3), 406-413.
48. Setayesh, M., Zhang, M., & Johnston, M. (2013). A novel particle swarm optimisation approach to detecting continuous, thin and smooth edges in noisy images. *Information Sciences*, *246*, 28-51.
49. Setayesh, M., Johnston, M., & Zhang, M. (2010, December). Edge and corner extraction using particle swarm optimisation. In *Australasian Joint Conference on Artificial Intelligence* (pp. 323-333). Springer, Berlin, Heidelberg.
50. Verma, O. P., Hanmandlu, M., Sultania, A. K., & Parihar, A. S. (2013). A novel fuzzy system for edge detection in noisy image using bacterial foraging. *Multidimensional Systems and Signal Processing*, *24*(1), 181-198.
51. Nearchou, A. C. (2011). Maximizing production rate and workload smoothing in assembly lines using particle swarm optimization. *International Journal of Production Economics*, *129*(2), 242-250.
52. Chen, A. L., Yang, G. K., & Wu, Z. M. (2006). Hybrid discrete particle swarm optimization algorithm for capacitated vehicle routing problem. *Journal of Zhejiang University-Science A*, *7*(4), 607-614.
53. Zhang, J. R., Zhang, J., Lok, T. M., &Lyu, M. R. (2007). A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training. *Applied mathematics and computation*, *185*(2), 1026-1037.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

54. Rashidi, M. M., Ali, M., Freidoonimehr, N., & Nazari, F. (2013). Parametric analysis and optimization of entropy generation in unsteady MHD flow over a stretching rotating disk using artificial neural network and particle swarm optimization algorithm. *Energy*, *55*, 497-510.
55. Chau, K. W. (2006). Particle swarm optimization training algorithm for ANNs in stage prediction of Shing Mun River. *Journal of hydrology*, *329*(3-4), 363-367.
56. Sun, J., Fang, W., Wu, X., Xie, Z., & Xu, W. (2011). QoS multicast routing using a quantum-behaved particle swarm optimization algorithm. *Engineering Applications of Artificial Intelligence*, *24*(1), 123-131.
57. Huang, C. J., Chuang, Y. T., & Hu, K. W. (2009). Using particle swam optimization for QoS in ad-hoc multicast. *Engineering Applications of Artificial Intelligence*, *22*(8), 1188-1193.
58. Vahedi, E., Zoroofi, R. A., & Shiva, M. (2012). Toward a new wavelet-based watermarking approach for color images using bio-inspired optimization principles. *Digital Signal Processing*, *22*(1), 153-162.
59. Das, M. T., &Dulger, L. C. (2007, November). Off-line signature verification with PSO-NN algorithm. In *2007 22nd international symposium on computer and information sciences* (pp. 1-6). IEEE.
60. AlRashidi, M. R., & El-Hawary, M. E. (2009). A survey of particle swarm optimization applications in electric power systems. *IEEE transactions on evolutionary computation*, *13*(4), 913-918.
61. AlRashidi, M. R., & El-Hawary, M. E. (2007). Hybrid particle swarm optimization approach for solving the discrete OPF problem considering the valve loading effects. *IEEE transactions on power systems*, *22*(4), 2030-2038.
62. Chiam, S. C., Tan, K. C., & Mamun, A. A. (2009). A memetic model of evolutionary PSO for computational finance applications. *Expert Systems with Applications*, *36*(2), 3695-3711.
63. Baykasoğlu, A., Özbakır, L., &Tapkan, P. (2007). Artificial bee colony algorithm and its application to generalized assignment problem. In *Swarm intelligence, focus on ant and particle swarm optimization*. IntechOpen.
64. Karaboga, D., &Basturk, B. (2008). On the performance of artificial bee colony (ABC) algorithm. *Applied soft computing*, *8*(1), 687-697.
65. Palanisamy, S., &Kanmani, S. (2012). Artificial bee colony approach for optimizing feature selection. *International Journal of Computer Science Issues (IJCSI)*, *9*(3), 432.
66. Karaboga, D., &Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of global optimization*, *39*(3), 459-471.
67. Holland J (1975) Adaptation in natural and artificial systems. The University of Michigan Press, Ann Arbor
68. Mitchell, M., Forrest, S., & Holland, J. H. (1992, December). The royal road for genetic algorithms: Fitness landscapes and GA performance. In Proceedings of the first European conference on artificial life (pp. 245-254). Cambridge: The MIT Press.
69. Akay, B., & Demir, K. (2019). Artificial Bee Colony Algorithm Variants and Its Application to Colormap Quantization. In *Evolutionary and Swarm Intelligence Algorithms* (pp. 25-41). Springer, Cham.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

70. Karaboga, D., Akay, B., & Ozturk, C. (2007, August). Artificial bee colony (ABC) optimization algorithm for training feed-forward neural networks. In *International conference on modeling decisions for artificial intelligence* (pp. 318-329). Springer, Berlin, Heidelberg.
71. Crawford, B., Soto, R., Cuesta, R., & Paredes, F. (2014). Application of the artificial bee colony algorithm for solving the set covering problem. *The Scientific World Journal*, *2014*.
72. Abu-Mouti FS, El-Hawary ME (2009) Modified artificial bee colony algorithm for optimal distributed generation sizing and allocation in distribution systems. In: Electrical power energy conference (EPEC), 2009 IEEE, pp 1–9
73. Akay B, Karaboga D (2010) A modified artificial bee colony algorithm for real-parameter optimization. Inf Sci.
74. Akay B, Karaboga D (2012) Artificial bee colony algorithm for large-scale problems and engineering design optimization. J Intell Manuf.
75. Alzaqebah M, Abdullah S (2011a) Artificial bee colony search algorithm for examination timetabling problems. Int J Phys Sci 6(17): 4264–4272
76. Alzaqebah M, Abdullah S (2011c) Hybrid artificial bee colony search algorithm based on disruptive selection for examination timetabling problems. In: Wang W, Zhu X, Du DZ (eds) Combinatorial optimization and applications. Lecture notes in computer science, vol 6831. Springer Berlin, pp 31–45
77. Arsuaga-Rios M, Vega-Rodriguez MA, Prieto-Castrillo F (2011) Multi-objective artificial bee colony for scheduling in grid environments. In: 2011 IEEE symposium on swarm intelligence (SIS), pp 1–7
78. Ayan K, Kılıç U (2011a) Comparison of ga, ma and abc algorithm for solution of optimal power flow. In: 6th international advanced technologies symposium (IATS11), Elazığ, Turkey, pp 13–18
79. Banharnsakun A, Achalakul T, Sirinaovakul B (2010a) Abc-gsx: A hybrid method for solving the traveling salesman problem. In: 2010 second world congress on nature and biologically inspired computing (NaBIC), pp 7–12
80. Benala TR, Jampala SD, Villa SH, Konathala B (2009) A novel approach to image edge enhancement using artificial bee colony optimization algorithm for hybridized smoothening filters. In: Abraham A, Herrera F, Carvalho A, Pai V (eds) 2009 world congress on nature and biologically inspired computing (NABIC 2009), pp 1070–1075
81. Bernardino A, Bernardino E, Snchez-Prez J, Gmez-Pulido J, Vega-Rodrguez M (2010) Efficient load balancing for a resilient packet ring using artificial bee colony. In: Di Chio C, Brabazon A, Di Caro G, Ebner M, Farooq M, Fink A, Grahl J, Greenfield G, Machado P, ONeill M, Tarantino E, Urquhart N (eds) Applications of evolutionary computation. Lecture notes in computer science, vol 6025. Springer, Berlin, pp 61–70
82. Unger, R., &Moult, J. (1993). Genetic algorithms for protein folding simulations. *Journal of molecular biology*, *231*(1), 75-81.

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

83. Smith, J. M., & Szathmary, E. (2019). Simulation of Biology. *Simulation*, *3*, 5.
84. El-Shorbagy, M. A., Ayoub, A. Y., Mousa, A. A., & El-Desoky, I. M. (2019). An enhanced genetic algorithm with new mutation for cluster analysis. *Computational Statistics*, 1-38.
85. Li, W., Zhou, Q., Ren, J., & Spector, S. (2019). Data mining optimization model for financial management information system based on improved genetic algorithm. *Information Systems and e-Business Management*, 1-19.
86. Edelstein, M., Ezuz, D., & Ben-Chen, M. (2019). A Genetic Algorithm for Fully Automatic Non-Isometric Shape Matching. *arXiv preprint arXiv:1905.10763*.
87. Williams, D., Zheng, Y., Davey, P. G., Bao, F., Shen, M., & Elsheikh, A. (2016). Reconstruction of 3D surface maps from anterior segment optical coherence tomography images using graph theory and genetic algorithms. *Biomedical Signal Processing and Control*, *25*, 91-98.
88. Fister Jr, I., Yang, X. S., Fister, I., Brest, J., &Fister, D. (2013). A brief review of nature-inspired algorithms for optimization. *arXiv preprint arXiv:1307.4186*.
89. Kumar, S., Singh, A., &Walia, S. (2018). Parallel Big Bang–Big Crunch Global Optimization Algorithm: Performance and its Applications to routing in WMNs. *Wireless Personal Communications*, *100*(4), 1601-1618.
90. El Aziz, M. A., &Hassanien, A. E. (2018). Modified cuckoo search algorithm with rough sets for feature selection. *Neural Computing and Applications*, *29*(4), 925-934.
91. Omran, M. G., Engelbrecht, A. P., & Salman, A. (2006). Particle swarm optimization for pattern recognition and image processing. In *Swarm intelligence in data mining* (pp. 125-151). Springer, Berlin, Heidelberg.
92. Davis, L. (1991). Handbook of genetic algorithms.
93. Ferentinos, K. P., Arvanitis, K. G., &Sigrimis, N. (2002). Heuristic optimization methods for motion planning of autonomous agricultural vehicles. *Journal of Global Optimization*, *23*(2), 155-170.
94. Dorigo, M., Bonabeau, E., & Theraulaz, G. (2000). Ant algorithms and stigmergy. Future Generation Computer Systems, 16(8), 851-871.
95. Merkle, D., & Middendorf, M. (2000, April). An ant algorithm with a new pheromone evaluation rule for total tardiness problems. In Workshops on Real-World Applications of Evolutionary Computation (pp. 290-299). Springer, Berlin, Heidelberg.
96. Sha, D. Y., & Lin, H. H. (2010). A multi-objective PSO for job-shop scheduling problems. Expert Systems with Applications, 37(2), 1065-1070.
97. Erol, K., & Eksin, I. (2006). A new optimization method: Big Bang–Big crunch. Advances in Engineering Software, 37, 106–111.
98. Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization (PSO). In Proc. IEEE International Conference on Neural Networks, Perth, Australia (pp. 1942-1948).

ISSN: 0971-1260
Vol-22-Issue-17-September-2019

99. Shi, Y., & Eberhart, R. (1998, May). A modified particle swarm optimizer. In 1998 IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence (Cat. No. 98TH8360) (pp. 69-73). IEEE.

100.van Zyl, E. T., & Engelbrecht, A. P. (2016, July). Group-based stochastic scaling for PSO velocities. In 2016 IEEE Congress on Evolutionary Computation (CEC) (pp. 1862-1868).

101. IEEE.Karaboga, D. (2010). Artificial bee colony algorithm. scholarpedia, 5(3), 6915.