International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 6, Issue 6, June 2016)

Natural Computing Algorithms – A Survey

Bharat V. Chawda[1], Dr. Jayeshkumar Madhubhai Patel[2]

[1]*Ph.D. Research Scholar, Gujarat Technological University, Ahmedabad, Gujarat, India*
[2]*Associate Professor, MCA Programme, Ganpat University, Kherva, Gujarat, India*

***Abstract* — Nature has efficiently provided solutions to complex real world problems since millenniums. This has inspired researchers to develop algorithms based on phenomena in the natural world. Such algorithms are referred as natural computing algorithms. Having the ability to provide optimal solutions to the real world problems, researchers have developed a number of different natural computing algorithms and their variations in the last couple of years. Some of these algorithms are widely known such as Genetic Algorithms, Simulated Annealing, Ant Colony Optimization, Particle Swarm Optimization, Firefly Algorithm, etc. In contrast to these, other algorithms are not known that much such as Fish Swarm Algorithm, Social Cognitive Optimization, Plant Propagation Algorithm, Krill Herd, Grey Wolf Optimizer, etc. This paper attempts to provide readers a comprehensive summary of all the natural computing algorithms developed as early as in the 1970s to the recent ones.**

***Keywords* — Natural Computing Algorithm (NCA), Nature Inspired Algorithm (NIA), Clever Algorithm (CA)**

I. INTRODUCTION

Nature has solved real-world complex problems using simple approaches applying in systematic manners. This has instigated many researchers to mimic the nature in technology – resulting in the development of Natural Computing Algorithms (NCAs). Natural computing algorithms are computer algorithms whose design draws inspiration from phenomena in the natural world [1]. They are also referred as nature-inspired algorithms (NIAs), or, clever algorithms (CAs). They have proved themselves to provide optimal solutions in reasonable time duration for a broad range of optimization problems.

Natural computing algorithms work on mainly two principles [2]: Exploration – which generates diverse solutions and explores search space, and, Exploitation – which strives to improve the quality of generated solutions. Both of these principles are applied iteration by iteration to find optimal solutions. There are mainly four factors behind the wide acceptance of the NCAs [3]. Natural computing algorithms are simple and flexible, use derivation-free mechanisms, and can avoid local minima.

According to the No Free Lunch (NFL) theorem [4], all problems cannot be solved by a single NCA. As a result, different researchers have developed different natural computing algorithms and their variations.

The remainder of this paper is organized as follows: Section II summarizes natural computing algorithms. Section III discusses various natural computing algorithms along with their inspirations. And, section IV provides a conclusion for the paper.

II. SUMMARY OF NATURAL COMPUTING ALGORITHMS

This section presents the summary of the various natural computing algorithms, developed in as early as the 1970s to recent ones, as given in table 1. This table lists various algorithms in a chronological order according to their initial proposal time. This table also includes widely used abbreviations for these algorithms along with names of researchers and publication years.

III. NATURAL COMPUTING ALGORITHMS

Genetic Algorithm (GA) [5]–[7] is inspired by Darwin's theory of evolution. It mimics the process of natural selection for survival of the fittest individual. GA is a population-based NCA that applies various operators such as Selection, Crossover and Mutation [70], [71].

Simulated Annealing (SA) [8], [9], [72] is inspired by the cooling process of a molten metal. Annealing schedule of a temperature and time duration for which system is to be evolved plays an important role in determining the quality of the solution.

Memetic Algorithm (MA) [10], [73] is based on a cultural revolution. It extends GA by applying local search to the individual solution to improve solution quality.

Ant Colony Optimization (ACO) [11], [74] is inspired by a foraging behavior of real ants. Ants possess natural ability to find the shortest tour between the food source and their nest. If a problem can be converted to a graph, ACO can be applied to find the optimum solution.

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 6, Issue 6, June 2016)

TABLE I
NATURAL COMPUTING ALGORITHMS – A SUMMARY

Abbreviation	Algorithm	Author(s)	Year	Ref
GA	Genetic Algorithm	Holland	1973 1975 1992	[5]–[7]
SA	Simulated Annealing	Kirkpatrick, Gelatt, Vecchi	1983 1997	[8], [9]
MA	Memetic Algorithm	Moscato	1989	[10]
ACO	Ant Colony Optimization	Dorigo, Colorni	1991	[11]
GP	Genetic Programming	Koza	1992	[12]
PSO	Particle Swarm Optimization	Kennedy, Eberhart	1995	[13]
DE	Differential Evolution	Storn, Price	1997	[14]
BEA	Bacterial Evolutionary Algorithm	Nawa, Furuhashi	1999	[15]
AIS	Artificial Immune System	Dasgupta	1999 2003	[16][17]
ES	Evolution Strategies	Beyer, Schewefel	2002	[18]
BFO	Bacterial Foraging Optimization	Passino	2002	[19]
FSA	Fish Swarm Algorithm	Li, Shao, Qian	2003	[20]
SFLA	Shuffled Frog Leaping Algorithm	Eusuff, Lansey	2003 2006	[21], [22]
SCO	Social Cognitive Optimization	Xie, Zhang	2004	[23]
IWCO	Invasive Weed Colony Optimization	Mehrabian, Lucas	2006	[24]
ABC	Artificial Bee Colony	Karaboga, Basturk	2005 2007	[25], [26]
GSO	Group Search Optimization	He, Wu, Saunders	2006	[27]
CFO	Central Force Optimization	Formato	2007 2008	[28], [29]
RFD	River Formation Dynamics	Rabanal, Rodriguez, Rubio	2007 2009	[30], [31]
IWD	Intelligent Water Drops	Shah-Hosseini	2007	[32]
RIO	Roach Infestation Optimization	Havens, Spain, Salmon, Keller	2008	[33]
MS	Monkey Search	Zhao, Tang	2008	[34]
BBO	Biogeography-Based Optimization	Simon	2008	[35]
LCA	League Championship Algorithm	Kashan	2009	[36]
GSO	Glowworm Swarm Optimization	Krishnanand, Ghose	2009	[37]
BBMO	Bumble Bees Mating Optimization	Marinakis, Marinaki, Matsatsinis	2009	[38]
HSO	Hunting Search Optimization	Oftadeh, Mahjoob	2009	[39]
FA	Firefly Algorithm	Yang	2009	[40]

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 6, Issue 6, June 2016)

TABLE I(CONTINUES)

Abbreviation	Algorithm	Author(s)	Year	Ref
HS	Harmony Search	Yang	2009	[41]
PFA	Paddy Field Algorithm	Premaratne, Samarabandu, Sidhu	2009	[42]
GSA	Gravitational Search Algorithm	Rashedi, Nezamabadi-Pour, Saryazdi	2009	[43]
CS	Cuckoo Search	Yang, Deb	2009 2010	[44], [45]
BIA	Bat Inspired Approach	Yang	2010	[46]
FA	Fireworks Algorithm	Tan, Zho	2010	[47]
PPA	Plant Propagation Algorithm	Salhi, Fraga	2011	[48]
CAB	Collective Animal Behavior	Cuevas, González, Zaldivar, Pérez-Cisneros, García	2012	[49]
WCA	Water Cycle Algorithm	Eskandar, Sadollah, Bahreininejad, Hamdi	2012	[50]
KH	Krill Herd	Gandomi, Alavi	2012	[51]
BCO	Bacterial Colony Optimization	Niu, Wang	2012	[52]
LA	Lion's Algorithm	Rajakumar	2012	[53]
SCO	Stem Cells Optimization	Taherdangkoo, Yazdi, Bagheri	2012	[54]
BNMR	Blind Naked Mole-Rats Algorithm	Shirzadi, Bagheri	2012	[55]
FPA	Flower Pollination Algorithm	Yang	2012 2014	[56], [57]
BH	Black Hole	Hatamlou	2013	[58]
CA	Cuttlefish Algorithm	Eesa, Abdulazeez, Orman	2013	[59]
MBA	Mine Blast Algorithm	Sadollah, Bahreininejad, Eskandar, Hamdi	2013	[60]
SSO	Social Spider Optimization	Cuevas, Cienfuegos, Zaldívar, Pérez-Cisneros	2013	[61]
SMO	Spider Monkey Optimization	Bansal, Sharma, Jadon, Clerc	2014	[62]
AMO	Animal Migration Optimization	Li, Zhang, Yin	2014	[63]
BMO	Bird Mating Optimizer	Askarzadeh	2014	[64]
FOA	Forest Optimization Algorithm	Ghaemi, Feizi-Derakhshi	2014	[65]
GWO	Grey Wolf Optimizer	Mirjalili, Mirjalili, Lewis	2014	[3]
VSA	Vortex Search Algorithm	Doğan, Ölmez	2015	[66]
WWO	Water Wave Optimization	Zheng	2015	[67]
EHO	Elephant Herding Optimization	Gai-Ge Wang	2015	[68]
RRO	Raven Roosting Optimization	Brabazon, Cui, O'Neill	2016	[69]

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 6, Issue 6, June 2016)

Genetic Programming (GP) [12] can be considered as an extension of GA. It uses a tree-structured representation for solutions with a varied length.

Particle Swarm Optimization (PSO) [13] is inspired by the flocking behavior of birds. It applies an iterative approach, where, in each iteration, a candidate solution (referred as a particle) is moved around in search space based on its position and velocity.

Differential Evolution (DE) [14] applies genetic evolution with mutation as arithmetic combinations of individuals.

Bacterial Evolutionary Algorithm (BEA) [15] is based on a microbial evolution phenomenon among bacteria along with gene transfer operation which allows chromosomes to directly transfer information to other chromosomes in a population.

Artificial Immune System (AIS) [16][17] is inspired by the principles and processes of the human immune system. Characteristics of the immune systems, such as learning and memory for use in problem-solving, are used by AIS.

Evolution Strategies (ES) [18] belongs to the category of evolutionary computation of artificial evolution methodologies. It applies adaptation and evolution by means of natural selection. Bacterial Foraging Optimization (BFO) [19] is inspired by the foraging behavior of bacteria. It focuses on the chemotactic (foraging) behavior of E. coli bacteria which lives in human intestines.

Fish Swarm Algorithm (FSA) [20], [75] is inspired by schooling behavior of fish. It uses concepts of collective movement of fish and social behavior to search food, immigration and to deal with dangers. Shuffled Frog Leaping Algorithm (SFLA) [21], [22] is inspired by the interactive behavior and global exchange of information of frogs, searching for food laid on discrete stones randomly located in a pond.

Social Cognitive Optimization (SCO) [23] is inspired by the social cognitive theory of humans which includes processes such as individual learning based on own memory as well as social learning.

Invasive Weed Colony Optimization (IWCO) [24] is based on the ecological process of weed colonization and distribution. Artificial Bee Colony (ABC) [25], [26] is inspired by the intelligent foraging behavior of honey bee swarm. Group Search Optimization (GSO) [27] is inspired by the animal searching behavior and group living theory.

Central Force Optimization (CFO) [28], [29] is based on the metaphor of the gravitational kinematics and particle motion in a gravitational field. River Formation Dynamics (RFD) [30], [31], [76] is inspired based on how rivers are formed in nature due to movement of water drops that transform the landscape.

Intelligent Water Drops (IWD) [32] is based on the actions and reactions that take place between water drops in the river and the changes that happen in the environment that river is flowing.

Roach Infestation Optimization (RIO) [33] is inspired by the social behavior of cockroaches. Monkey Search (MS) [34] is inspired by the mountain climbing process of monkeys that consists of climb process, watch-jump process, and somersault process. Biogeography-Based Optimization (BBO) [35] is based on the study of geographical distribution of biological organisms.

League Championship Algorithm (LCA) [36] is based on the competition of sports teams in a league championship. Glowworm Swarm Optimization (GSO) [37] is based on the behavior of glowworms which possess the capability to change the intensity of luciferin emission. Bumble Bees Mating Optimization (BBMO) [38] simulates the mating behavior that swarm of bumble bees performs. Hunting Search Optimization (HSO) [39] is inspired by the group hunting behavior of animals such as lions and wolves.

Firefly Algorithm (FA) [40] is inspired based on flashing behavior of fireflies which is used as a signal system to attract other fireflies. Harmony Search (HS) [41] is inspired by the improvisation process of musicians. Paddy Field Algorithm (PFA) [42] is based on a reproduction of a plant population in a field applying the concept of a plant closure to the optimum solution will produce more seeds. Gravitational Search Algorithm (GSA) [43] is inspired by the law of gravity and mass interactions. Cuckoo Search (CS) [44], [45] is inspired by the breeding behavior of cuckoos in which cuckoos lay color-pattern mimicked eggs in nests of other birds.

Bat Inspired Approach (BIA) [46] is inspired by the echolocation behavior of bats. Fireworks Algorithm (FA) [47] is based on explosion process of fireworks and mechanisms for maintaining the diversity of sparks.

Plant Propagation Algorithm (PPA) [48] is inspired by the propagation of plants – particularly plants like that of strawberry in which the maiden plant sends runners which, upon touching the ground, grow roots from which daughter plants emerge and propagation continues.

Collective Animal Behavior (CAB) [49] is based on the collective behavior of different animal groups such as swarming, milling, migrating in aligned groups. Water Cycle Algorithm (WCA) [50] is based on real world water cycle among transpiration/evaporation, condensation, and precipitation. Krill Herd (KH) [51] is based on the simulation of herding behavior of krill individuals which depends on movement induced by other individuals, foraging activity, and random diffusion.

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 6, Issue 6, June 2016)

Bacterial Colony Optimization (BCO) [52] is inspired by the behavior of E. coli bacteria at different development stages in their life cycle. Lion's Algorithm (LA) [53] is based on the social behavior of lions that helps to keep themselves strong among others. Stem Cells Optimization (SCO) [54] is based on reproduction behavior of stem cells.

Blind Naked Mole-Rats Algorithm (BNMR) [55] is inspired by the social behavior of blind naked mole-rats colony in searching the food and protecting the colony against invasions. Flower Pollination Algorithm (FPA) [56], [57] is based on the pollination process of flowering plants.

Black Hole (BH) [58] is inspired by the star swallowing process of black holes. Cuttlefish Algorithm (CA) [59] is based on the mechanism of color changing behavior adopted by the cuttlefish. Mine Blast Algorithm (MBA) [60] is inspired by the concept of mine bomb explosion. Social Spider Optimization (SSO) [61] is based on the simulation of the cooperative behavior of social spiders.

Spider Monkey Optimization (SMO) [62] is inspired by the foraging behavior of spider monkeys which use a fission-fusion social structure based on the scarcity or availability of food. Animal Migration Optimization (AMO) [63] is inspired by the behavior of animals during migration from one location to another location along with some animals leave the group while some join the group.

Bird Mating Optimizer (BMO) [64] is based on the mating strategies of birds and imitates the behavior of bird species metaphorically to breed broods with superior genes. Forest Optimization Algorithm (FOA) [65] is inspired by the seeding procedure used by the trees in a forest for better survival. Grey Wolf Optimizer (GWO) [3] is based on the leadership hierarchy and hunting mechanism used by the grey wolves.

Vortex Search Algorithm (VSA) [66] is inspired by the vortex pattern created by the vertical flow of the stirred fluids. Water Wave Optimization (WWO) [67] is based on the propagation, refraction and breaking phenomena of shallow water waves. Elephant Herding Optimization (EHO) [68] is based on the herding behavior of elephant groups and utilizes two main operators named clan updating operator and separating operator.

Raven Roosting Optimization (RRO) [69] is inspired by the social roosting and foraging behavior of one species of a bird called common raven.

IV. Conclusion

Real world problems are becoming more and more complex day by day. Traditional methods cannot solve them within the reasonable time duration.

As an alternative, natural computing algorithms have provided satisfactory solutions within feasible time limits. This paper began with the introduction of NCAs. A comprehensive list of various NCAs has been listed in a tabular format which could be a one-point-stop for readers to get an overview of these algorithms. After this, each of these algorithms is introduced based on the inspiration taken from nature. This discussion can be helpful to researchers to provide a base for further research work in the area of natural computing.

Future work can focus on a specific algorithm(s) and their variations in the form of extensive research based on the problem to be solved.

REFERENCES

[1] J. Dang, A. Brabazon, D. Edelman, and M. O'Neill, "An Introduction to Natural Computing in Finance," in Applications of Evolutionary Computing, M. Giacobini, A. Brabazon, S. Cagnoni, G. A. D. Caro, A. Ekárt, A. I. Esparcia-Alcázar, M. Farooq, A. Fink, and P. Machado, Eds. Springer Berlin Heidelberg, 2009, pp. 182–192.

[2] X.-S. Yang, Nature-inspired metaheuristic algorithms. Luniver press, 2010.

[3] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," Adv. Eng. Softw., vol. 69, pp. 46–61, 2014.

[4] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," Evol. Comput. IEEE Trans. On, vol. 1, no. 1, pp. 67–82, 1997.

[5] J. H. Holland, "Genetic algorithms and the optimal allocation of trials," SIAM J. Comput., vol. 2, no. 2, pp. 88–105, 1973.

[6] J. H. Holland, Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. U Michigan Press, 1975.

[7] J. H. Holland, Adaptation in Natural and Artificial Systems. Cambridge, MA, USA: MIT Press, 1992.

[8] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," SCIENCE, vol. 220, no. 4598, pp. 671–680, 1983.

[9] D. Bookstaber, Simulated Annealing for Traveling Salesman Problem. Spring, 1997.

[10] P. Moscato, On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts - Towards Memetic Algorithms. 1989.

[11] A. Colorni, M. Dorigo, V. Maniezzo, and others, "Distributed optimization by ant colonies," in Proceedings of the first European conference on artificial life, 1991, vol. 142, pp. 134–142.

[12] J. R. Koza, Genetic Programming: On the Programming of Computers by Means of Natural Selection. Cambridge, MA, USA: MIT Press, 1992.

[13] J. Kennedy and R. Eberhart, "Particle swarm optimization," in , IEEE International Conference on Neural Networks, 1995. Proceedings, 1995, vol. 4, pp. 1942–1948 vol.4.

[14] R. Storn and K. Price, "Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces," J. Glob. Optim., vol. 11, no. 4, pp. 341–359, 1997.

[15] N. E. Nawa and T. Furuhashi, "Fuzzy system parameters discovery by bacterial evolutionary algorithm," Fuzzy Syst. IEEE Trans. On, vol. 7, no. 5, pp. 608–616, 1999.

[16] D. DasGupta, Artificial immune systems and their applications. Springer Publishing Company, Incorporated, 2014.

[17] D. Dasgupta, Z. Ji, F. A. González, and others, "Artificial immune system (AIS) research in the last five years.," in IEEE Congress on Evolutionary Computation (1), 2003, pp. 123–130.

[18] H.-G. Beyer and H.-P. Schwefel, "Evolution strategies–A comprehensive introduction," Nat. Comput., vol. 1, no. 1, pp. 3–52, 2002.

[19] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," IEEE Control Syst., vol. 22, no. 3, pp. 52–67, Jun. 2002.

[20] X. Li and J. Qian, "Studies on Artificial Fish Swarm Optimization Algorithm based on Decomposition and Coordination Techniques [J]," J. Circuits Syst., vol. 1, pp. 1–6, 2003.

[21] M. M. Eusuff and K. E. Lansey, "Optimization of water distribution network design using the shuffled frog leaping algorithm," J. Water Resour. Plan. Manag., vol. 129, no. 3, pp. 210–225, 2003.

[22] M. Eusuff, K. Lansey, and F. Pasha, "Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization," Eng. Optim., vol. 38, no. 2, pp. 129–154, 2006.

[23] X.-F. Xie and W.-J. Zhang, "Solving engineering design problems by social cognitive optimization," in Genetic and Evolutionary Computation–GECCO 2004, 2004, pp. 261–262.

[24] A. R. Mehrabian and C. Lucas, "A novel numerical optimization algorithm inspired from weed colonization," Ecol. Inform., vol. 1, no. 4, pp. 355–366, 2006.

[25] D. Karaboga, "An idea based on honey bee swarm for numerical optimization," Technical report-tr06, Erciyes university, engineering faculty, computer engineering department, 2005.

[26] D. Karaboga and B. Basturk, "A Powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) Algorithm," J Glob. Optim., vol. 39, no. 3, pp. 459–471, Nov. 2007.

[27] S. He, Q. H. Wu, and J. R. Saunders, "A novel group search optimizer inspired by animal behavioural ecology," in Evolutionary Computation, 2006. CEC 2006. IEEE Congress on, 2006, pp. 1272–1278.

[28] R. A. Formato, "Central force optimization: a new metaheuristic with applications in applied electromagnetics," Prog. Electromagn. Res., vol. 77, pp. 425–491, 2007.

[29] R. A. Formato, "Central force optimization: a new nature inspired computational framework for multidimensional search and optimization," in Nature Inspired Cooperative Strategies for Optimization (NICSO 2007), Springer, 2008, pp. 221–238.

[30] P. Rabanal, I. Rodríguez, and F. Rubio, "Using river formation dynamics to design heuristic algorithms," in Unconventional Computation, Springer, 2007, pp. 163–177.

[31] P. Rabanal, I. Rodríguez, and F. Rubio, "Applying river formation dynamics to solve NP-complete problems," in Nature-inspired algorithms for optimisation, Springer, 2009, pp. 333–368.

[32] H. Shah-Hosseini, "Problem solving by intelligent water drops," in IEEE Congress on Evolutionary Computation, 2007. CEC 2007, 2007, pp. 3226–3231.

[33] T. C. Havens, C. J. Spain, N. G. Salmon, and J. M. Keller, "Roach infestation optimization," in Swarm Intelligence Symposium, 2008. SIS 2008. IEEE, 2008, pp. 1–7.

[34] R. Zhao and W. Tang, "Monkey algorithm for global numerical optimization," J. Uncertain Syst., vol. 2, no. 3, pp. 165–176, 2008.

[35] D. Simon, "Biogeography-Based Optimization," IEEE Trans. Evol. Comput., vol. 12, no. 6, pp. 702–713, Dec. 2008.

[36] A. H. Kashan, "League championship algorithm: a new algorithm for numerical function optimization," in 2009 International Conference of Soft Computing and Pattern Recognition, 2009, pp. 43–48.

[37] K. N. Krishnanand and D. Ghose, "Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions," Swarm Intell., vol. 3, no. 2, pp. 87–124, 2009.

[38] Y. Marinakis, M. Marinaki, and N. Matsatsinis, "A hybrid bumble bees mating optimization-grasp algorithm for clustering," in Hybrid Artificial Intelligence Systems, Springer, 2009, pp. 549–556.

[39] R. Oftadeh and M. J. Mahjoob, "A new meta-heuristic optimization algorithm: Hunting Search," in Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control, 2009. ICSCCW 2009. Fifth International Conference on, 2009, pp. 1–5.

[40] X.-S. Yang, "Firefly algorithms for multimodal optimization," in Stochastic algorithms: foundations and applications, Springer, 2009, pp. 169–178.

[41] X.-S. Yang, "Harmony Search as a Metaheuristic Algorithm," in Music-Inspired Harmony Search Algorithm, Z. W. Geem, Ed. Springer Berlin Heidelberg, 2009, pp. 1–14.

[42] U. Premaratne, J. Samarabandu, and T. Sidhu, "A new biologically inspired optimization algorithm," in 2009 International Conference on Industrial and Information Systems (ICIIS), 2009, pp. 279–284.

[43] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: a gravitational search algorithm," Inf. Sci., vol. 179, no. 13, pp. 2232–2248, 2009.

[44] X.-S. Yang and S. Deb, "Cuckoo search via Lévy flights," in Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on, 2009, pp. 210–214.

[45] X.-S. Yang and S. Deb, "Engineering optimisation by cuckoo search," Int. J. Math. Model. Numer. Optim., vol. 1, no. 4, pp. 330–343, 2010.

[46] X.-S. Yang, "A New Metaheuristic Bat-Inspired Algorithm," in Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), J. R. González, D. A. Pelta, C. Cruz, G. Terrazas, and N. Krasnogor, Eds. Springer Berlin Heidelberg, 2010, pp. 65–74.

[47] Y. Tan and Y. Zhu, "Fireworks Algorithm for Optimization," in Advances in Swarm Intelligence, Y. Tan, Y. Shi, and K. C. Tan, Eds. Springer Berlin Heidelberg, 2010, pp. 355–364.

[48] A. Salhi and E. S. Fraga, "Nature-inspired optimisation approaches and the new plant propagation algorithm," 2011.

[49] E. Cuevas, M. González, D. Zaldivar, M. Pérez-Cisneros, and G. García, "An algorithm for global optimization inspired by collective animal behavior," Discrete Dyn. Nat. Soc., vol. 2012, 2012.

[50] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, "Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems," Comput. Struct., vol. 110, pp. 151–166, 2012.

[51] A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," Commun. Nonlinear Sci. Numer. Simul., vol. 17, no. 12, pp. 4831–4845, Dec. 2012.

[52] B. Niu and H. Wang, "Bacterial colony optimization," Discrete Dyn. Nat. Soc., vol. 2012, 2012.

[53] B. R. Rajakumar, “The Lion’s Algorithm: A New Nature-Inspired Search Algorithm,” Procedia Technol., vol. 6, pp. 126–135, 2012.

[54] M. Taherdangkoo, M. Yazdi, and M. H. Bagheri, “Stem Cells Optimization Algorithm,” in Bio-Inspired Computing and Applications, D.-S. Huang, Y. Gan, P. Premaratne, and K. Han, Eds. Springer Berlin Heidelberg, 2012, pp. 394–403.

[55] M. T. M. H. Shirzadi and M. H. Bagheri, “A novel meta-heuristic algorithm for numerical function optimization: blind, naked mole-rats (BNMR) algorithm,” Sci. Res. Essays, vol. 7, no. 41, pp. 3566–3583, 2012.

[56] X.-S. Yang, “Flower pollination algorithm for global optimization,” in Unconventional computation and natural computation, Springer, 2012, pp. 240–249.

[57] X.-S. Yang, M. Karamanoglu, and X. He, “Flower pollination algorithm: a novel approach for multiobjective optimization,” Eng. Optim., vol. 46, no. 9, pp. 1222–1237, 2014.

[58] A. Hatamlou, “Black hole: A new heuristic optimization approach for data clustering,” Inf. Sci., vol. 222, pp. 175–184, Feb. 2013.

[59] A. S. Eesa, A. M. Abdulazeez, and Z. Orman, “Cuttlefish algorithm–a novel bio-inspired optimization algorithm,” Int. J. Sci. Eng. Res., vol. 4, no. 9, pp. 1978–1986, 2013.

[60] A. Sadollah, A. Bahreininejad, H. Eskandar, and M. Hamdi, “Mine blast algorithm: A new population based algorithm for solving constrained engineering optimization problems,” Appl. Soft Comput., vol. 13, no. 5, pp. 2592–2612, May 2013.

[61] E. Cuevas, M. Cienfuegos, D. Zaldívar, and M. Pérez-Cisneros, “A swarm optimization algorithm inspired in the behavior of the social-spider,” Expert Syst. Appl., vol. 40, no. 16, pp. 6374–6384, 2013.

[62] J. C. Bansal, H. Sharma, S. S. Jadon, and M. Clerc, “Spider monkey optimization algorithm for numerical optimization,” Memetic Comput., vol. 6, no. 1, pp. 31–47, 2014.

[63] X. Li, J. Zhang, and M. Yin, “Animal migration optimization: an optimization algorithm inspired by animal migration behavior,” Neural Comput. Appl., vol. 24, no. 7–8, pp. 1867–1877, 2014.

[64] A. Askarzadeh, “Bird mating optimizer: An optimization algorithm inspired by bird mating strategies,” Commun. Nonlinear Sci. Numer. Simul., vol. 19, no. 4, pp. 1213–1228, Apr. 2014.

[65] M. Ghaemi and M.-R. Feizi-Derakhshi, “Forest optimization algorithm,” Expert Syst. Appl., vol. 41, no. 15, pp. 6676–6687, 2014.

[66] B. Doğan and T. Ölmez, “A new metaheuristic for numerical function optimization: Vortex Search algorithm,” Inf. Sci., vol. 293, pp. 125–145, 2015.

[67] Y.-J. Zheng, “Water wave optimization: A new nature-inspired metaheuristic,” Comput. Oper. Res., vol. 55, pp. 1–11, Mar. 2015.

[68] S. D. Gai-Ge Wang, “Elephant Herding Optimization,” 2015.

[69] A. Brabazon, W. Cui, and M. O’Neill, “The raven roosting optimisation algorithm,” Soft Comput., vol. 20, no. 2, pp. 525–545, Jan. 2015.

[70] K. Sastry, D. E. Goldberg, and G. Kendall, “Genetic algorithms,” in Search methodologies, Springer, 2014, pp. 93–117.

[71] N. Sureja and B. Chawda, “Random Traveling Salesman problem using Genetic Algorithms,” IFRSA’s Int. J. Comput., vol. 2, no. 2, 2012.

[72] N. Sureja and B. Chawda, “Random Travelling Salesman Problem using SA,” Int. J. Emerg. Technol. Adv. Eng., vol. 2, no. 4, 2012.

[73] N. M. Sureja and B. V. Chawda, “Memetic Algorithm a Metaheuristic Approach to Solve RTSP,” IJCSEITR ISSN, pp. 2249–6831, 2013.

[74] B. V. Chawda and N. M. Sureja, “An ACO Approach to Solve a Variant of TSP,” Int. J. Adv. Res. Comput. Eng. Technol. IJARCET, vol. 1, no. 5, p. pp–222, 2012.

[75] M. Neshat, G. Sepidnam, M. Sargolzaei, and A. N. Toosi, “Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial and indicative applications,” Artif. Intell. Rev., vol. 42, no. 4, pp. 965–997, May 2012.

[76] S. S. Shah, P. B. Swadas, and B. V. Chawda, “Travelling Salesman Problem Solutions using Various Heuristic Algorithms,” in International Conference on Information, Knowledge & Research in Engineering, Technology & Sciences - 2012, Rajkot, Gujarat, India, 2012, pp. 1142–1145.