Literature Review on Differential Evolution Algorithm

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Abstract

Differential evolution algorithm is one of the most efficient metaheuristic approaches. In this paper, a review and analysis is presented in order to help for future research in differential evolution algorithm. It covers an analysis of about 142 papers of the previous work in the modifications of the algorithm including the main parameters of the classical steps of the algorithm and hybridization with other algorithms. The analysis also shows the applications that optimized using the differential evolution algorithm.

1. Introduction

Metaheuristic is an old Greek word that contains two words. The first one is the word Meta, which means high level. The second word is Heuristic, which means to search. In operations research and artificial intelligence, the word metaheuristic is related to finding solutions of the optimization problems using random search and local search. The history of metaheuristics return back to 1950 (Sörensen et al., 2018). This paper discusses a review on one of the metaheuristic approaches called differential evolution algorithm. Such algorithm is developed by Storn and Price(Storn & Price, 1996). The differential evolution algorithm begins by generating population of candidate solutions. The solutions are obtained by combining the existing solutions in the population using a simple formula. Then the algorithm determine whichever solution is the best. The differential evolution algorithm seems very like the genetic algorithm in its steps, where it utilizes the current solutions in the population by mutating them and using crossover techniques.Figure 1 shows the flowchart of the differential evolution algorithm.The paper is organized in four sections as follows. Section 2 shows the literature review of the differential evolution algorithm. Section 3 shows the analysis of the literature review. Section 4 presents the conclusion.

2. Literature review

DE performance is confined by specified mutation and crossover strategies and the associated control parameters (mutation scale factor F, crossover constant CR and population size NP). Therefore, researchers have been adapting modern techniques to improve the performance and to overcome problems of classic DE. In this section, a literature review is presented to show the previous work that developed on the DE algorithm. The section contains three sub-sections. The first one presents the previous work that developed to modify the classic DE. The second sub-section shows the previous work that presented on the hybridization with the other algorithms. The third section shows the applications that solved using DE.

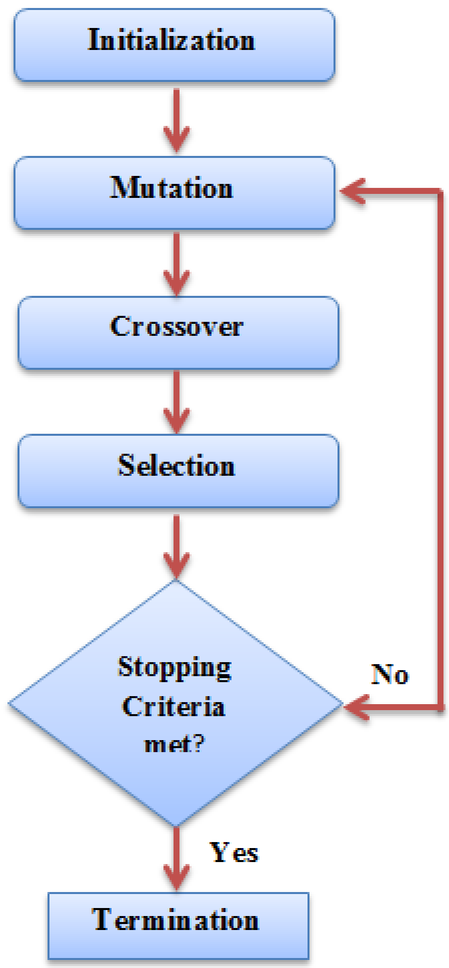

Figure 1: The flowchart of the differential evolution algorithm

2.1. Modifications of the classic DE

This sub-section shows the previous work presented in the modifications of DE. Qin, Huang, and Suganthan(2008) proposed a self-adaptive DE (SaDE) algorithm, in which both trial vector generation strategies and their associated control parameter values are gradually selfadapted by learning from their previous experiences in generating promising solutions. Das et al.(2009)suggestedtwo types of topological local DE models to attainproper ratiobetween the explorative and exploitative techniques of DE, called DEGL. Two trail vectors were generated by mutating the global and local neighborhood and combined to formulate an actual trial vector by employing a weight factor.Gong et al. (Gong et al., 2010)presented a family of improved DE that attempts to adaptively choose a more suitable strategy.Brest and Maucec(Brest & Maučec, 2011)proposed a ‘self-adaptive differential evolution algorithm’ called jDElscop.

Mallipeddi et al.(2011)developed the so-called EPSDE, self-adaptive DE, which relies on ensemble approach. A group of distinct mutation approaches with a group of values for each control parameters are generated and competed to each other through the evaluation process to produce better outcomes.Wang, Cai, and Zhang(2011)introduced a composite DE (CoDE) approach which randomly combines three strategies of trial vectors generation alongside using three control parameters settings. L. Wang et al. (2012) proposed a novel modified binary differential evolution algorithm (NMBDE). Caraffini et al.(2013)proposed a memetic strategy called (SMADE), Super-fit Multi-criteria Adaptive DE based on the Multi-criteria Adaptive DE (MADE). Tanabe and Fukunaga(2013)proposed parameter adaptation that is based on the historical memory of the successful control parameter settings to guide the values of the future control parameters. Tanabe and Fukunaga(Tanabe & Fukunaga, 2014) developed an adaptation of DE using linear population size reduction that decreases the population size gradually using linear function.Cortés-Antonio et al.(2014) presents the results of implementation of differential evolution algorithm on a field programmable gate array device (FPGA) using floating point representation with double precision.Ali Wagdy Mohamed(Ali Wagdy Mohamed, 2015) introduced a triangular mutation rule based on convex combination vector.Wu et al. (Wu et al., 2016)introduced a multi-population-based structure to identify an adapted collection of threemutation strategies. The population is dynamically dividedinto severalsub-populations includingone reward sub-population and three indicator sub-populations. Each sub-population’s indicator, with a comparativelysmaller size, is assigned to acomponentmutation strategy, while the reward sub-population, with a relatively larger size,is allocated to the current-best performed mutationapproach as an extra reward. Consequently, an allocation of dynamic computational source among themutation strategiesis created.

Ali W Mohamed et al.(2017)modified of Tanabe and Fukunaga(Tanabe & Fukunaga, 2014) algorithm by utilizing different adaption approach for the selection of control parameters.Ali Wagdy Mohamed(2017) introduced a study to measure the difference between the worst and the best solutions at a generation. They combined directed mutation rule with the improved basic mutation technique. The study objective was to increase the ability of local search of the basic DE and to obtain a better balance between robustness and convergence rate. Akararungruangkul & Kaewman(2018) modified two points in the original DE, which are the mutation formula is introduced and the rule of local search.Ali W. Mohamed et al. (Ali W. Mohamed et al., 2019)demonstrated a new triangular mutation rule relies on the convex integration vector of the three randomly selected vectors as well as the difference vector between the worst and best individuals among the triple stochastic vectors.Meng et al. (2019)proposed an algorithm, which is pointed to address some of the weaknesses of classic DE and the improved ones. Such as, lack in a given mutation approach and inappropriate control parameters adaptation schemes.

Stanovov et al.(2020) proposeda new parameter control scheme for the differential evolution algorithm. The developed linear bias reduction scheme controls the Lehmer mean parameter value depending on the optimization stage allowing the algorithm to improve the exploration properties at the beginning of the search and speed up the exploitation at the end of the search. As a basic algorithm, the L-SHADE approach is considered, as well as its modifications, namely the jSO and DISH algorithms.Centeno-Telleria et al. (2021) to present a consistent methodology for tuning optimal parameters. At the heart of the methodology is the use of an artificial neural network (ANN) that learns to draw links between the algorithm performance and parameter values. Table 1: Different Modification of DE .

Table 1: Different Modification of DE.

Contribution	NO. of Contribution	Year
Population	2	2014, 2016
Learning procedures	9	2010, 2011, 2012, 2013, 2014, 2016, 2017, 2020
Mutation functions	8	2009, 2011, 2015, 2016, 2017, 2018, 2019
control parameters	8	2008, 2011, 2013, 2017, 2019, 2020, 2021
Vector generation	4	2008, 2009, 2011

2.2. Hybridization with other algorithms

This sub-section shows the literatures review about the recent published researches hybridization of DE Algorithm with other algorithms.where Hybridization is another important modification in DE which is implemented to enhance its performance and convergence speed. Plenty of work can be found in the literature on the hybridization of DE. Pant et al. (2008) also proposed a hybrid version of DE with particle swarm optimization and results show that the proposed DE-PSO is quite competent for solving the considered test functions as well as real-life problems.Ali et al. (2009)hybridized the Ant Colony Algorithm with DE and applied it on problems related to water resources. Gong et al. (2010) proposed a hybridization between DE and biography-based optimization (BBO). The method produced a noticeable result through integration of BBO exploitation with DE exploration. X. Wang and Xu (2011)proposed hybrid DE Algorithm that uses hill climbing heuristic for solving traveling salesman problem.Gao andLiu (2011)developed a hybridization betweenthe artificial bee colony and DE algorithms.El Dor et al. (2012) hybridized particle swarm optimization with DE for enhancing the algorithm.

Cui et al.(2013) proposed a hybrid differential evolution harmony search algorithm for numerical optimization problems.Rahmat and Musirin (2013)presented a differential evolution immunized ant colony optimization technique in solving economic load dispatch problem. Fister Jr et al. (2013) proposed a hybrid bat algorithm with the DE algorithm. Saruhan (2014) proposed differential evolution and simulated annealing algorithms for mechanical systems design. Addawe and Magadia (2014)proposed differential evolution and simulated annealing algorithms for fitting autoregressive models to data. Fouad (2014)proposed a novel hybrid genetic differential evolution algorithm for constrained optimization problems.Sabar et al. (2015)developedhybrid DEalgorithm that uses game theoryto control the selection of mutation parameters during the search process. X. Meng et al.(2015) proposed a hybrid bat algorithm with DEalgorithm for constrained optimization problems. Sarbazfard and Jafarian(2016) presented ahybrid algorithm based on firefly algorithm and DE for global optimization problems. Z. Zhang et al. ((2016) hybridized cuckoo search and krill herd optimization with DE.

Mlakar et al. (2016)proposed a hybrid differential evolution by using a switchingprobability strategy of Cuckoo search and applied it for multi-level image thresholding.MohammadZadeh and Sadjadi(2017) presented a hybrid firefly and DE algorithm for optimization of a mixed repairable and non-repairable system reliability problem.Jadon et al. (2017)used a hybrid artificial bee colony algorithm with DE. Nama and Saha(2018)proposed a hybrid DE algorithm with backtracking search optimization algorithm for solving optimization problems.Chen et al.(2018) proposed a hybrid expert system based on sleep event's threshold dependencies for automated personalized sleep staging by combining symbolic fusion and DE algorithm.Zhang et al. (2018) presented Differential-Evolution-Based Coevolution Ant Colony Optimization Algorithm for Bayesian Network Structure Learning. Naz et al. (Naz et al., 2018) introduced a hybrid gray wolf differential evolution algorithm to minimize the peak load demand electricity cost. Z. Zhang et al. (2019) used a hybrid optimization algorithm based on cuckoo search and differential evolution for solving constrained engineering problems.Liu et al. (2019)presented a hybrid differential evolution based on the random walk of ants around the ant lion is presented, which combines the advantages of ant lion optimization algorithm and differential evolution, aiming to well balance the exploitation and exploration of the search.Reddy(2019)proposed an approach for solving the optimal power flow problem using hybrid DE with harmony search algorithm.Chi et al. (2019)presented a hybridization of cuckoo search and differential evolution for the logistics distribution center location problem.Sethanan and Jamrus (2020) presented a hybrid differential evolution algorithm involving a genetic operator with fuzzy logic controller for solving the multi-trip vehicle routing problem with backhauls and a heterogeneous fleet.Pan et al. (2020) presented a hybrid differential evolution algorithm combining two previous modified DE algorithms. M. Liu et al.(2020) a hybrid whale optimization algorithm enhanced with Levy flight and differential evolution. Ahmadianfar et al.

(2021)developed a hybrid DE with particle swarm optimization algorithm for solving operating rules for multi-reservoir hydropower generation systems.Mohsin et al. (2021)proposed a hybrid optimization algorithm based on DE and grey wolf optimizer. Ding et al. (2021) proposed a hybridized algorithm between the differential evolution and black hole algorithms.

2.3. Applications of DE

The DE since 1996 has become a very powerful method to solve a wide range of scientific problems, including computer science, physics, signal processing, shape optimization, control science, manufacturing, management, traffic control and economics (Shamekhi, 2013). In this sub-section, a literature review is presented to show the applications that were solved using DE. Table 2 shows the applications of DE in the electrical and power systems. Table 3 shows the applications of DE in the manufacturing science and operations research. Table 4 shows the applications of DE in the Robotics and Expert Systems. Table 5 shows the applications of DE in robotics and expert systems. Table 6 shows the applications of DE in pattern recognition. Table 7 shows the applications of DE in image processing. Table 8 shows the applications of DE in the bioinformatics and bio-medical engineering. Table 9 shows the applications of DE in electronics and communication engineering.Figure2shows diverging Radial graph of DE applications in different areas.

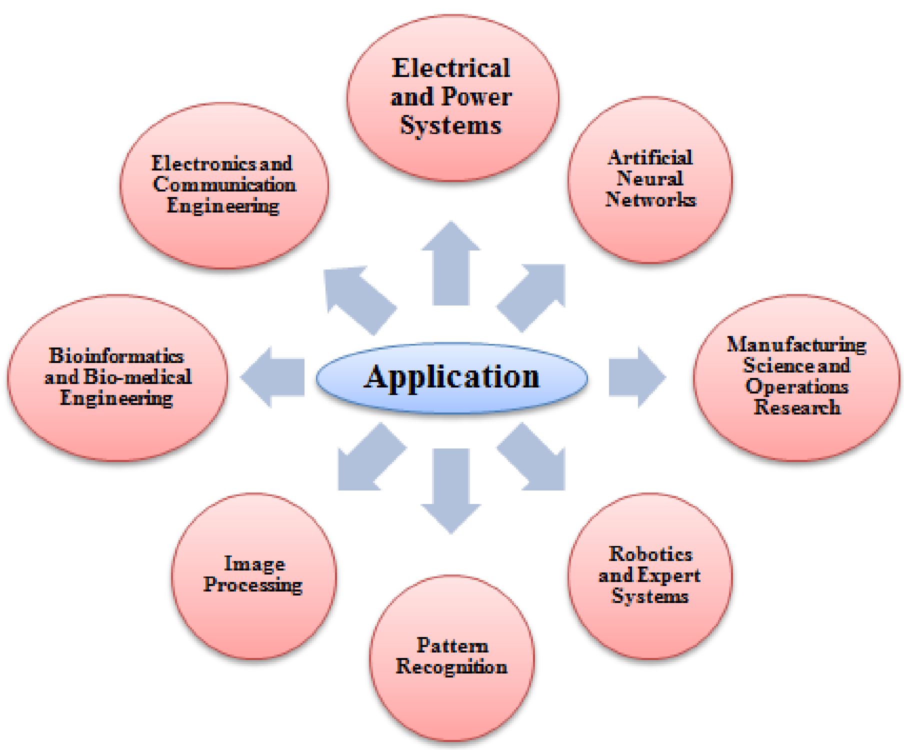

Figure 2: Diverging Radial graph of DE applications in different areas.

Table 2: Electrical and Power Systems

Authors	Applications
Bhattacharya and Chattopadhyay(2010)	Economic Dispatch
Basu(2011)	
Sayah and Hamouda(2011)	
Aktulga et al.(2012)	
Azad et al.(2012)	
Glotić and Zamuda(2015)	
Pandit et al.(2015)	
Ghasemi et al.(2016)	
Niu et al.(2014)	Power System Stabilizer
T. Wang et al.(2014)	Fault Diagnosis
Prado et al.(2014)	Power Distribution Reconfiguration
Sivasubramani and Swarup(2012)	Optimal Power Flow
Birogul(2019)	

Table 3: Artificial Neural Networks

Authors	Applications
Dragoi et al.(2013)	Optimal Network Topology
Singh et al.(2020)	
Dhahri et al. (2012)	Designing of Different Variants of Neural Networks
B. Wang et al.(2018)	
Balamurugan et al. (2021)	
Subudhi & Jena(2011)	Neural Network Training
Piotrowski(2014)	
Lu et al.(2012)	Fuzzy Neural Net Controller
U. P. Singh and Jain(2018)	Neural Network for Non linear System Identification

Table 4: Manufacturing Science and Operations Research

Authors	Applications
G. Zhang et al.(2013)	Manufacturing Process Optimization
Yildiz(2013a)	
Liao et al.(2012)	Transport Sequencing in Cross Docking Systems
Yildiz(2013b)	Optimization of Multi-Pass Turning Operations
Q.-K. Pan et al.(2011)	Scheduling
Vincent and Ponnambalam(2012)	
Ponsich and Coello(2013)	
W.-L. Wang et al.(2013)	
Tang et al.(2013)	

Authors	Applications
Glotić et al.(2014)	Scheduling
M. Liu et al.(2020)	
Zhao et al.(2014)	Ship route planning and marine safety
Jigang et al.(2019)	speed control of brushless direct-current motor

Table 5: Robotics and Expert Systems

Authors	Applications
Vasile et al.(2011)	Space Trajectory Optimization
Das et al.(2016)	Route Planning/Guidance of Unmanned Vehicles
Raghunathan and Ghose(2014)	
Zamuda and Sosa(2014)	
Y. Chen et al.(2015)	Satellite Orbit Reconfiguration
Cao et al.(2015)	Part based Work Piece Detection
Nyirarugira and Kim(2013)	Real Time Object Tracking
Ugolotti et al.(2013)	Object Detection
Ugolotti and Cagnoni(2013)	Body Pose Estimation
Hachicha et al.(2011)	Financial Market Dynamics
C.-H. Chen and Yang(2014)	Neural Fuzzy Inference System
Zamuda& Sosa(2019)	expert system for underwater glider path planning

Table 6: Pattern Recognition

Authors	Applications
Qasem and Shamsuddin(2011)	Classification
Luukka and Lampinen(2011)	
Triguero et al.(2011)	
Neri and Tirronen(2010)	
Garcı et al.(2012)	
Bencherif et al.(2014)	
Luo et al.(2015)	
Zhong et al.(2013)	Clustering
Lin et al.(2019)	
Kuo et al.(2013)	
Khushaba et al.(2011)	Feature Selection
Al-Ani et al.(2013)	
Nayak et al.(2020)	

Table 7: Image Processing

Authors	Applications
Das et al. (2009)	clusters in the image
Ghosh et al.(2014)	Moving Object Detection
Cruz-Aceves et al.(2013)	Image Segmentation
Ramadas et al.(2019)	
Ali et al.(2014)	Multi-level Image Thresholding
Sarkar et al.(2015)	
Al-Ani et al.(2013)	Feature Selection in Image Data
Casella et al.(2019)	Range Image Registration
Xu et al.(2014)	Sub-pixel Mapping
Zamuda et al.(2011)	Animated Tree Reconstruction
Zamuda and Brest(2014)	
Kang et al.(2013)	3D Reconstruction from Uncalibrated Images
Dhabal et al.(2021)	Image clarification
Guraksin et al.(2019)	

Table 8: Bioinformatics and Bio-medical Engineering

Authors	Applications
Ali, Ahn, and Siarry(2014)	Hypoglycemia Detection
De Falco(2013)	Rule Extraction from Medical Database
Lei et al.(2014)	
Mesejo et al.(2013)	Hippocampus localization in histological images
Sannino et al.(2014)	Monitoring of obstructive sleep
Zhan et al.(2014)	Parameter Estimation of Biological Systems

Table 9: Electronics and Communication Engineering

Authors	Applications
Almeida-Luz et al.(2011)	Mobile Location Management
Chang(2012)	Non-linear System Modeling
Kuila and Jana(2014)	Clustering of Wireless Sensory Network
Gundry et al.(2015)	Mobile Ad-hoc Networks
Li et al.(2013)	Optimal Fault Protection in Networks
Baraldi et al.(2016)	
Lezama et al.(2012)	Placement of Wavelength Convertors.

Authors	Applications
Sengupta et al.(2012)	Sleep-scheduling in wireless sensor networks
R. Li et al.(2011)	Electromagnetics including antenna design
Secmen and Tasgetiren(2011)	

3. The Analysis of The literature review

This section presents an analysis of the review through analyzing the modifications done in the parameters of the algorithm, the applications that were solved using the algorithm, and the number of publications and their categories.

3.1. The modifications of the parameters of DE

The analysis begins by showing a list of modifications as seen inTable 10. The modificationscan be classified into five criteria, which are population, learning procedures, mutation functions, control parameters, and vector generation.Figure 2 shows a bar chart that visually shows the results of Table 10. The figure shows that Mallipeddi et al. (Mallipeddi et al., 2011), Wang et al. (Y. Wang et al., 2011), and Wu et al. (Wu et al., 2016) have presented the top number of modifications in the parameters of the algorithm.Figure 3 shows the percentage of modifications in the parameters of the algorithm. The figure shows that the lowest percentage of modificationsin parameters are in vector generation and population criteria. Figure 4 shows the percentage of publications of the modifications of the parameters of the algorithm.

Table 10: The list of modifications for each author

Author	Modifications
Qin, Huang, and Suganthan(2008)	Vector generation
	control parameters
Das et al.(2009)	Vector generation
	Mutation functions
Gong et al.(Gong et al., 2010)	Learning procedures
Brest and Maucec(Brest & Maučec, 2011)	Learning procedures
Mallipeddi et al.(2011)	Mutation functions
	control parameters
	Vector generation
Wang, Cai, and Zhang(2011)	Learning procedures
	Vector generation
	control parameters
L. Wang et al. (2012)	Learning procedures
Caraffini et al.(2013)	Learning procedures
Tanabe and Fukunaga(2013)	control parameters
Tanabe and Fukunaga(Tanabe & Fukunaga, 2014)	Population

Author	Modifications
Cortés-Antonio et al.(2014)	Learning procedures
Ali Wagdy Mohamed(Ali Wagdy Mohamed, 2015)	Mutation functions
Wu et al. (Wu et al., 2016)	Population
	Mutation functions
	Learning procedures
Ali W Mohamed et al.(2017)	Learning procedures
	control parameters
	Mutation functions
Akararungruangkul & Kaewman(2018)	Mutation functions
Ali W. Mohamed et al. (Ali W. Mohamed et al., 2019)	Mutation functions
Meng et al. (2019)	Mutation functions
	control parameters
Stanovov et al. (2020)	control parameters
	Learning procedures
Centeno-Telleria et al. (2021)	control parameters

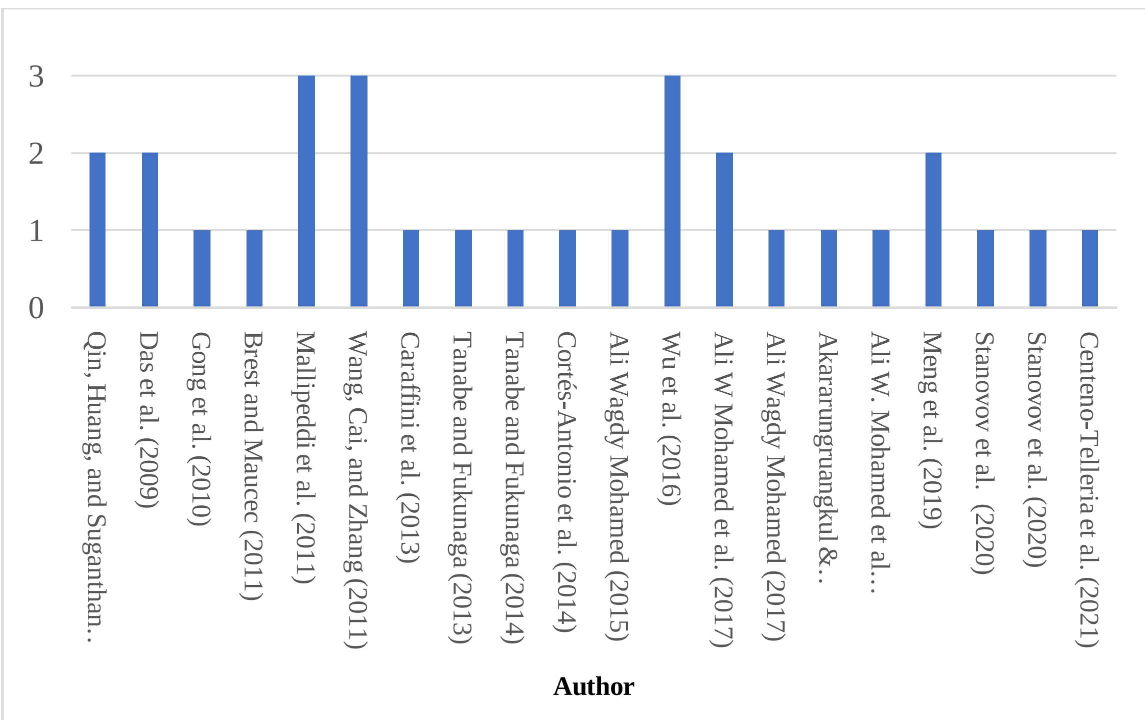

Figure 3: The relationship between authors and their modifications

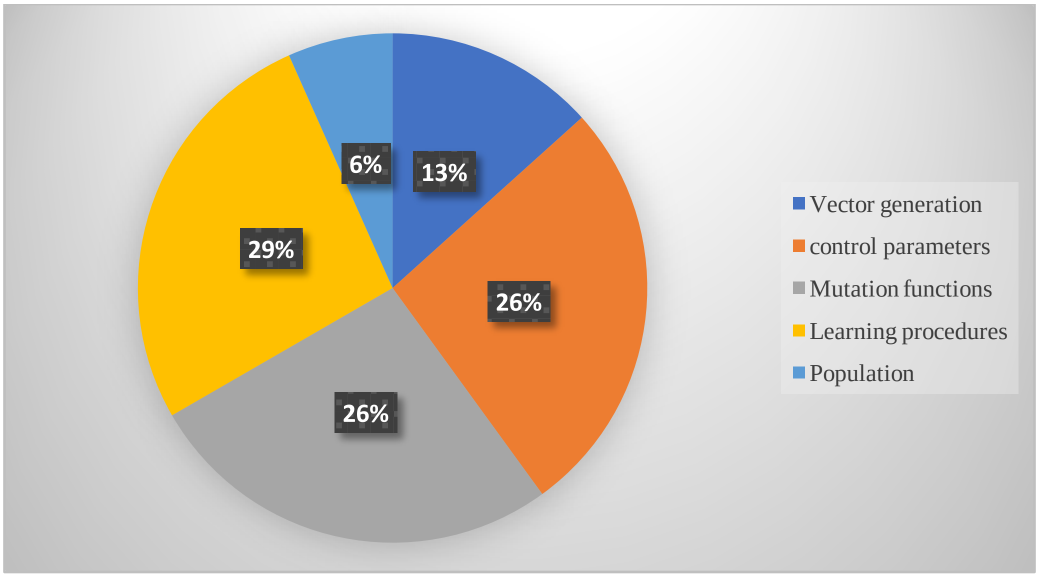

Figure 4: The percentage of modifications in parameters of DE

3.2. The hybridization of DE with other algorithms

This sub-section shows the algorithm that were hybridized with DE. Table 11 shows the hybridized approaches with DE in the previous work.

Table 11: The hybridized approaches with DE

Hybridization	**The percentage of researches**
Ant colony Optimization.	9%
The Ant Lion Optimizer.	6%
Artificial bee colony algorithm.	6%
Cuckoo search algorithm.	12%
Bat Algorithm.	9%
Firefly's Algorithm.	6%
Harmony search Algorithm.	6%
Simulated annealing Algorithm.	6%
Genetic Algorithm.	12%
Grey wolf optimizer.	3%
Whale optimization algorithm	3%
Particle swarm optimization algorithm	9%
BlackHole algorithms	3%
Biography-based optimization	6%
Hill climbing	3%

3.3. Applications Solved Using DE

Figure 5 shows the percentage of the previous work of the applications that were solved using DE.

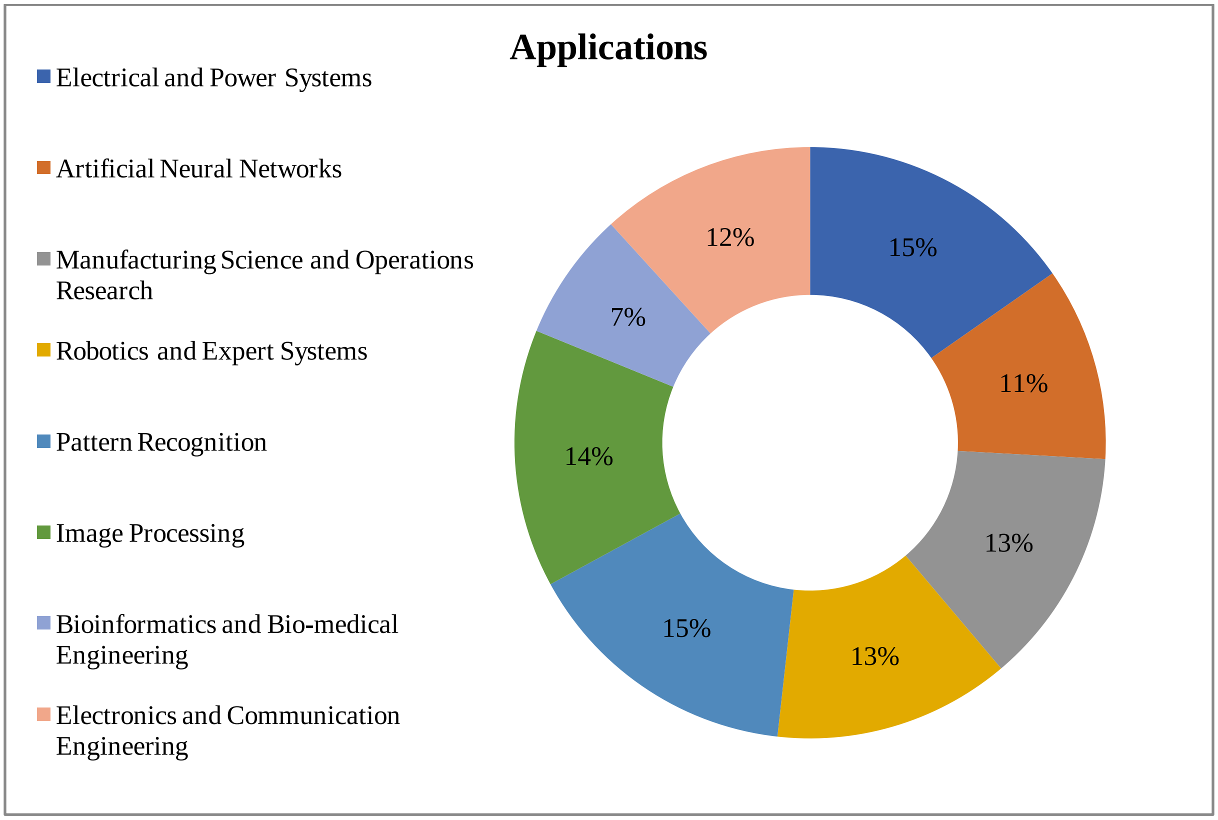

Figure 5:The percentage of publication according to applications of DE.

3.4. Publication by Year

Figure 6 shows the number of published papers per year in DE from 2008 to 2021.

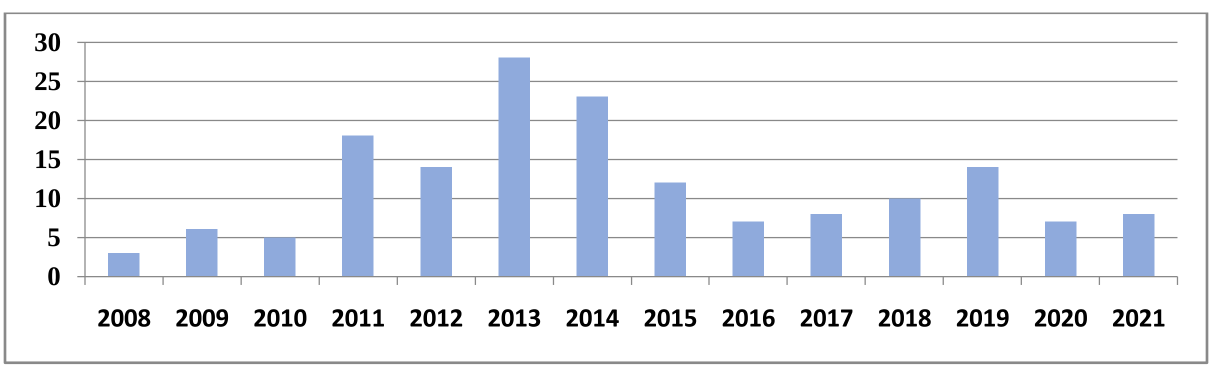

Figure 6:The number of Publications per year

4. Conclusion

This study presents a review on differential evolution algorithm. The analysis of the review could help the researchers to have a clear view about the previous work through analyzing the modifications of the parameters or the algorithm, the hybridized approaches with DE, the applications that were solved using DE and the number of publications from 2008 to 2021. The analysis shows that Mallipeddi et al. (Mallipeddi et al., 2011), Wang et al. (Y. Wang et al., 2011), and Wu et al. (Wu et al., 2016) have presented the top number of modifications in the parameters of the algorithm. The analysis also shows that the lowest percentage of modifications in parameters are in vector generation and population parameters. Therefore, the recommendation in this point for future work is to have a highly focus on both of these parameters. Table 12 shows the hybridized approaches with DE. The researchers simply could hybridize some other algorithms that are not included in such table. The number published papers in DE until 2021 shows that such approach is still having special concentration from researchers as seen in figure 6.

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