Sādhanā (2026)51:34
https://doi.org/10.1007/s12046-025-03028-x

Adaptive switching heuristic based evolutionary algorithm: design, validation and comparison

TEJAS M VALA[1], VIPUL N RAJPUT[2,*], KEVIN JOSHI[3], KARTIK S PANDYA[4] and SANTOSH C VORA[5]

[1]Department of Electrical Engineering, Government Engineering College, Godhra, Gujarat 389001, India
[2]Department of Electrical Engineering, Ipcowala Institute of Engineering and Technology, Dharmaj, Gujarat 388430, India
[3]Product Engineering and Research, Respirer Living Sciences Pvt. Ltd., Pune, Maharashtra 411007, India
[4]Department of Electrical Engineering, Parul University, Vadodara, Gujarat 391760, India
[5]Department of Electrical Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat 382481, India
e-mail: valatejasre@gmail.com; vipulrajput1616986@gmail.com; kevin@respirer.in; kartik.pandya30364@paruluniversity.ac.in; santoshvora@yahoo.com

MS received 25 October 2023; revised 16 August 2025; accepted 19 August 2025

Abstract. Innovations in data engineering, computational resource availability, and novel mathematical modeling approaches encourage research in optimization to provide promising solutions for a range of challenges in diverse fields. The need and advancements have thus led to researchers proposing evolutionary algorithms (EAs) to solve optimization challenges. However, specifically for EAs, mechanisms to address the global and local search strategies are vital for implementation and solution. To this end, we propose a formalized EA focusing on adaptive switching between global search and local search while leveraging the ε-constraint method for constraint handling. The proposed algorithm uses a novel switching parameter to heuristically switch between global search and local search based on objective function value. Diverse optimization test suites, including standard unconstrained test functions and CEC 2011 real world optimization problems, are used to compare the results of the proposed algorithm to other well-known EAs. In addition, CEC 2020 real world single objective constrained optimization problems are included in the experimental evaluation to prove the effectiveness of the proposed algorithm.

Keywords. Adaptive switching; evolutionary algorithm; global search; Local search; nonparametric tests; real world optimization problems.

1. Introduction

A range of new challenges arises due to the widespread adoption of automation, digital infrastructure, and data-based decision-making [1–4]. Consequently, the intricacy of real world problems rise significantly in the manufacturing, engineering, and applied domains [5–7]. Such challenges often seek solutions to maximize or minimize the value of an objective that mathematical modeling approaches can define [8–10]. Metaheuristic or Evolutionary algorithms (EAs), a particular class of predominantly nature-inspired optimization algorithms, receives wide attention for their ability to achieve optimal solutions by mimicking a natural phenomenon [11–13]. The advantages of parallel execution and progression, dynamic adaptability, random sampling, and non-prescriptive behavior contribute to its increasing suitability and implementation for solving complex real world optimization challenges [14, 15].

EAs have distinct global and local search strategies according to their natural inspirations or evolution concepts. The local search uses direct knowledge, whereas the global search employs a stochastic approach to find a solution. Hence, the performance of EAs is essentially a function of their effective global and local search strategies [16]. Some of these well-known algorithms are genetic algorithm (GA) [17], differential evolution (DE) [18], cuckoo search algorithm (CSA) [19], artificial bee colony (ABC) [20], firefly algorithm (FA) [21], bat algorithm (BA) [22], harmony search algorithm (HSA) [23] and particle swarm optimization (PSO) [24].

To solve complex optimization problems effectively, hybrid firefly and particle swarm optimization algorithm

*For correspondence
Published online: 27 January 2026

(HFPSO) is introduced in [25]. It is also compared with other hybrid algorithms such as FFPSO and HPSOFF, and robust variants of PSO such as EPSO and ISRPSO. A hybrid grey wolf optimizer-cuckoo search (GWOCS) is employed quantitatively to combine the beneficial aspects of both GWO and CS that identified optimal parameters of solid oxide fuel cell [26], load frequency controller design for comlpicated power networks [27] and solution of optimal power flow problem [28]. The particle swarm optimization gravitational search algorithm (PSOGSA) is introduced for the optimal dispatch of reactive power with distributed generation sources [29], for optimal distributed generator allocations [30] and for more applications. The method proposed in the work [31], is a dynamic neighborhood-based switching PSO variant with distance-based dynamic neighborhood and a switching learning strategy for adaptive acceleration. It increases accuracy and convergence when working on complex multimodal problems, but could add computational overhead and parameter tuning. Then [32] explores the dynamic algorithm selection (dynAS) in EAs, where switching between the algorithms has been reported to yield performance gains. It still has some limitations in consistently picking the best solvers and in solving dynAS completely, thus a detailed analysis of unsuccesful cases in single-objective optimization is required. In [33], an intelligent switch mechanism for discriminating the most suitable algorithm, for the problem landscape given its fitness landscape features, is presented. Although it performs better than classical single-algorithms, it is still essentially alternating between two algorithms and cannot adapt to different optimization landscapes. However [34] emphasizes switching based on

Table 1. Test suite implementation survey.

[37]	Functions	CEC 2011 (selective), CEC 2014 and constrained optimization problems
	Challenge	Finding local best solutions and issues with convergence rate for high-dimensional and some multimodal problems.
	Solution	MFO is integrated with orthogonal learning (OL) and Broyden-Fletcher-Goldfarb-Shanno (BFGS) to accelerate the performance of MFO.
[38]	Functions	CEC 2011 (selective), CEC 2014 and CEC 2017
	Challenge	Selection of PSO swarm size, population size crucially affect the performance.
	Solution	Performance of eight PSO variants for swarm sizes ranging from 3 up to 1000 particles.
[39]	Functions	CEC 2011 and optimize the design of propulsion unit for an electric vehicle (EV)
	Challenge	Adaptive control the parameters for DE to avoid getting trapped into a local minimum.
	Solution	A multi-criteria-based selection operator to balance the exploration and exploitation phases in addition to a restart strategy for early convergence.
[40]	Functions	CEC 2011 and CEC 2014
	Challenge	Recommendation for researchers and engineers to apply an algorithm to solve their real world optimization problems.
	Solution	Comparison of eleven popular swarm-based and bio-inspired algorithms with a random blind search and four variants of adaptive DE.
[41]	Functions	CEC 2011, CEC 2014 and 23 benchmark functions
	Challenge	In the case of large scale practical problems, the optimization effect of FOA may be unsatisfactory, and it is prone to stagnation.
	Solution	Enrich the exploration and exploitation capability of the classic FOA using a whale-inspired hunting strategy.
[42]	Functions	CEC 2011
	Challenge	Improve the classic ACO by balancing exploitation and exploration.
	Solution	Using a success-based random-walk selection that chooses between Brownian motion and Levy flights or local search is used to enhance solutions in the colony.
[43]	Functions	CEC 2011 (selective) and 14 standard functions
	Challenge	To utilize the information available from individuals in previous iterations.
	Solution	Incorporating different information feedback models into the updating process.
[44]	Functions	CEC 2011 (selective) and CEC 2017 (selective)
	Challenge	Gravitational search algorithm (GSA) exhibits low search performance and premature convergence.
	Solution	Hierarchical interactions among the population, iteration-best, personal-best and global-best layers are dynamically implemented in different search stages to improve both exploration and exploitation.
ASHEA	Functions	CEC 2011, CEC 2020 and 13 standard unconstrained problems
	Challenge	An effective mechanism to utilize the global search and local search
	Solution	To come up with a formalized algorithm capable of switching heuristically between effective global and local search strategies based on objective function value improvisation.

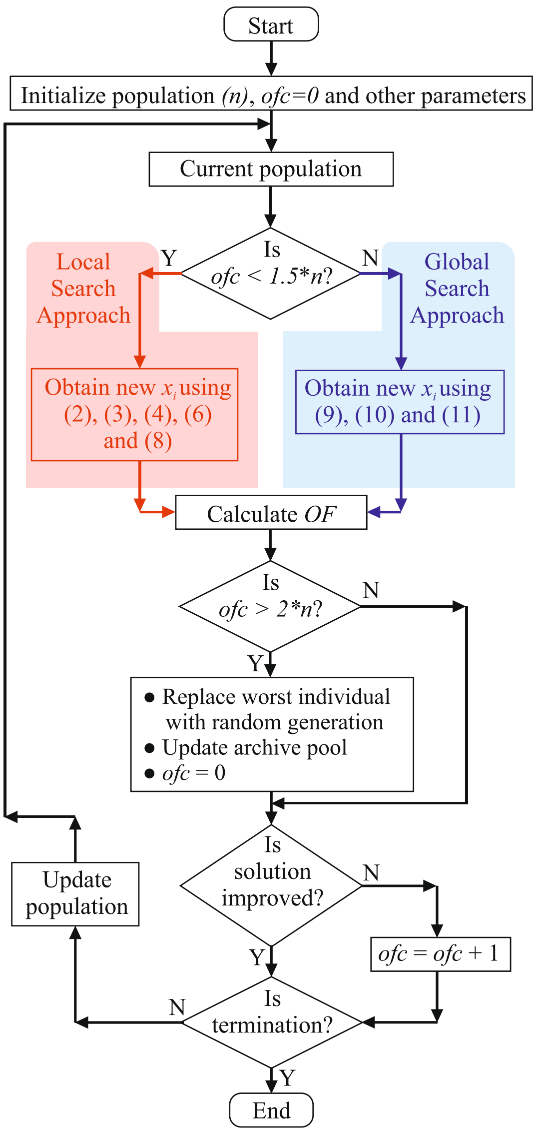

Figure 1. Generic diagram of ASHEA.

Begin
Initialize/define the parameters, *ofc = 0*
Random selection of the parameters S_{f1}, S_{f2}, M, σ and ψ throughout
Objective function $OF^t = f(X^t), X^t = (x_1, x_2, ..., x_D)^T$
While *(t < Max function evaluations)* (Algorithm starts with Local Search Approach first)
If *(ofc < C_l*n)*
Evaluate x_i using either of the following equations with equal probabilities
$x_i^{t+1} = x_{r1} + S_{f2}(x_{r2} - x_{r3}) + (1 - S_{f2})(x_{r4} - x_{r5})$
$x_i^{t+1} = x_i^t + S_{f2}(x_{best} - x_i^t) + (1 - S_{f2})(x_{r2} - x_0)$
$x_i^{t+1} = x_{best} + rand(x_{r1} - x_i^t) + (1 - S_{f2})(x_{r2} - x_{r3})$
$x_i^{t+1} = x_i^t + M(x_i^t - x_{best})$
$x_i^{t+1} = x_i^t + \sigma(x_j^t - x_i^t) + \psi$
Exchange variables randomly within newly generated population with lower probability of P_{el}
Else
Evaluate x_i using either of the following equations with equal probabilities
$x_i^{t+1} = x_i^t + M(x_i^t - x_{best})$
$x_i^{t+1} = x_i^t + S_{f1}(x_{r2,g} - x_{r3,g})$
$x_i^{t+1} = x_{best} + S_{f2}(x_i^t - x_{r3,g}) + (1 - S_{f2})(x_{r1,g} - x_{r2,g})$
Exchange variables randomly within newly generated population with probability of P_{eg}
End If
Merge parent and new population
Arrange them in ascending order of *OF* value and keep first *n* solutions
If *(ofc > C_g*n)*
ofc = 0
Replace worst individual with randomly generation
Push this rejected worst individual in the archive pool
End If
If *($OF(1)_{new} > OF(1)$)*
ofc = ofc + 1
End If
End While
Post process results and visualization
End

Figure 2. Pseudo code of ASHEA.

EAs, that efficiently changes their tactics and employs warm starting in order to improve performance on single-objective problems, it faces the overhead of frequent switching and the criteria with which they switch indicates information regarding the changes in landscapes. Dynamic algorithm selection guided by which features lie on the same trajectory is proposed in [35]. However, it only cares about switching performance and local switching strategy is proposed to improve the search efficiency. Though powe-ful, it can introduce complexity and may involve fine parameter tunning. Nevertheless, global search and local search depend on the previous population or the information available from the solution vector at a given iteration. Therefore, utilizing the knowledge from previous iterations in global search and local search is vital to obtain a feasible solution. The extension of utilizing such knowledge provides an opportunity to investigate adaptiveness in switching between global search and local search. The switching between global search and local search is to promote a better solution where adaptive and logical switching methodology is an integral part of the EA.

This work proposes a novel algorithm known as an adaptive switching heuristic based evolutionary algorithm (ASHEA) to address adaptive behavior between global search and local search. Hence, effective global and local search strategies are two primary components of ASHEA, incorporating an adaptive switching between global and local search strategies. Conventionally, novel optimization algorithms should perform well for solving standard optimization functions and real world challenges. Therefore, the trend to test the performance of a novel optimization algorithm for standard test functions and real world problems such as CEC competition test suites has become a norm. Table 1 presents the work reported by several researchers utilizing the standard CEC competition test suites of optimization problems [37–44].

Therefore, based on previous literature, this work aims to address the gaps with the following major contributions:

- Drawing upon the knowledge gained from previous iterations, an advanced optimization algorithm is developed that integrates a switching mechanism, seamlessly combining global search and local search strategies.

Table 2. Parameterization of EAs.

Parameters		ASHEA	GA	CSA	PSO	HSA
No. of function evaluations for unconstrained problems		10000	10000	10000	10000	10000
No. of function evaluations for CEC 2011 RWOPs		50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000
No. of function evaluations for CEC 2020 RWSOCOPS	D $\leq$ 10	100000	100000	100000	100000	100000
	10 D $\leq$ 30	200000	200000	200000	200000	200000
	30 D $\leq$ 50	400000	400000	400000	400000	400000
	50 D $\leq$ 150	800000	800000	800000	800000	800000
	150 D	1000000	1000000	1000000	1000000	1000000
Population size (n)		30	30	30	30	30
Control factors [Cl, Cg]		[1.5, 2]	–	–	–	–
Exchange Probabilities [Pel, Peg]		[0.05, 0.3]	–	–	–	–
Crossover		–	0.8	–	–	–
Mutation		–	0.2	–	–	–
Abandon Probability		–	–	0.25	–	–
Learning Factor (a)		–	–	–	–	–
Experience acceleration factors [c1, c2]		–	–	–	[2, 2]	–
Gravitational Constant (G0)		–	–	–	–	–
Harmony memory consideration rate (HMCR)		–	–	–	–	0.95
Pitch adjustment rate (PAR)		–	–	–	–	0.3
Loudness [Amax, Amin]		–	–	–	–	–
Pulse-rate [rmax, rmin]		–	–	–	–	–
Randomization parameter		–	–	–	–	–
Absorption coefficient		–	–	–	–	–
Scale factor		–	–	–	–	–
Crossover probability		–	–	–	–	–
Limit		–	–	–	–	–

Parameters	BA	FA	DE	ABC	HFPSO	GWOCS	PSOGSA
No. of function evaluations for unconstrained problems	10000	10000	10000	10000	10000	10000	10000
No. of function evaluations for CEC 2011 RWOPs	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000	50000, 100000, 150000
No. of function evaluations for CEC 2020 RWSOCOPS	100000	100000	100000	100000	100000	100000	100000

Table 2 continued

Parameters	BA	FA	DE	ABC	HFPSO	GWOCS	PSOGSA
	200000 400000 800000 1000000	200000 400000 800000 1000000	200000 400000 800000 1000000	200000 400000 800000 1000000	200000 400000 800000 1000000	200000 400000 800000 1000000	200000 400000 800000 1000000
Population size (n)	30	30	30	30	30	30	30
Control factors [Cl, Cg]	–	–	–	–	–	–	–
Exchange Probabilities [Pel, Peg]	–	–	–	–	–	–	–
Crossover	–	–	–	–	–	–	–
Mutation	–	–	–	–	–	–	–
Abandon Probability	–	–	–	–	–	0.25	–
Learning Factor (a)	–	–	–	–	–	[0, 2]	–
Experience acceleration factors [c1, c2]	–	–	–	–	[1.49, 1.49]	–	[0.5, 1.5]
Gravitational Constant (G0)	–	–	–	–	–	–	1
Harmony memory consideration rate (HMCR)	–	–	–	–	–	–	–
Pitch adjustment rate (PAR)	–	–	–	–	–	–	–
Loudness [Amax, Amin]	[1, 2]	–	–	–	–	–	–
Pulse-rate [rmax, rmin]	[0, 1]	–	–	–	–	–	–
Randomization parameter	–	0.25	–	–	0.2	–	–
Absorption coefficient	–	1	–	–	1	–	–
Scale factor	–	–	0.6	–	–	–	–
Crossover probability	–	–	0.8	–	–	–	–
Limit	–	–	–	nD/2	–	–	–

Table 3. EA-wise results for unconstrained optimization problems.

Test Problem (Global best)		ASHEA	GA	CSA	PSO	HSA	BA
Ackley (0)	Best	**8.882E-16**	4.699E-06	8.333E-06	3.506E-03	8.898E-06	8.882E-16
	Mean	1.030E-15	3.870E-01	1.836E-04	1.136E+00	2.102E+00	1.315E-15
	Standard deviation	7.033E-16	9.451E-01	2.018E-04	7.793E-01	1.456E+00	1.166E-15
Booth (0)	Best	**0.000E+00**	1.090E-12	2.022E-12	7.222E-04	8.863E-09	7.889E-31
	Mean	1.857E-14	5.689E-10	2.211E-10	3.012E-02	1.159E+00	1.494E-18
	Standard deviation	1.313E-13	6.675E-10	3.876E-10	3.955E-02	1.522E+00	1.054E-17
Branin (-0.397887)	Best	**3.979E-01**	3.979E-01	3.979E-01	3.979E-01	3.979E-01	3.979E-01
	Mean	**3.979E-01**	3.979E-01	3.979E-01	4.304E-01	4.057E-01	3.979E-01
	Standard deviation	3.617E-16	5.102E-10	2.120E-08	2.183E-01	1.795E-02	4.199E-15
Goldstein Price (-3)	Best	**3.000E+00**	3.000E+00	3.000E+00	3.000E+00	3.000E+00	3.000E+00
	Mean	**3.000E+00**	7.320E+00	3.000E+00	3.015E+00	6.142E+00	4.620E+00
	Standard deviation	4.641E-15	9.999E+00	8.195E-08	5.755E-02	7.339E+00	1.146E+01
Hump (0)	Best	**4.651E-08**	4.652E-08	4.651E-08	3.799E-05	4.652E-08	4.651E-08
	Mean	**4.651E-08**	1.632E-02	4.707E-08	9.953E-03	2.412E-03	4.651E-08
	Standard deviation	1.316E-16	1.154E-01	6.520E-10	9.352E-03	7.848E-03	1.803E-16
Matyas (0)	Best	**0.000E+00**	2.012E-13	3.252E-14	1.249E-05	8.273E-08	3.126E-187
	Mean	3.199E-23	6.694E-11	5.939E-12	1.615E-03	7.345E-02	**1.693E-135**
	Standard deviation	2.262E-22	2.503E-10	1.209E-11	1.901E-03	1.135E-01	**1.197E-134**
Perm (0)	Best	**0.000E+00**	3.650E-11	2.641E-14	1.576E-09	7.183E-07	0.000E+00
	Mean	1.143E-17	9.933E-07	1.111E-09	3.413E-02	4.108E-03	2.425E-08
	Standard deviation	8.083E-17	6.686E-06	2.312E-09	7.896E-02	4.909E-03	1.089E-07
Power Sum (0)	Best	**1.508E-09**	2.110E-05	5.988E-04	1.698E-01	3.191E-03	1.485E-05
	Mean	**1.120E-03**	5.644E-02	1.328E-02	3.364E-01	3.202E-01	1.034E-01
	Standard deviation	**3.295E-03**	5.748E-02	1.337E-02	5.489E-01	3.238E-01	1.791E-01
Rastrigin (0)	Best	**0.000E+00**	2.883E-11	2.469E-07	2.128E-06	3.764E-10	0.000E+00
	Mean	**0.000E+00**	5.373E-01	5.563E-05	1.513E-01	3.740E-01	9.950E-02
	Standard deviation	**0.000E+00**	9.473E-01	1.248E-04	3.181E-01	5.689E-01	4.144E-01
Sphere (0)	Best	**0.000E+00**	1.186E-13	5.807E-15	3.933E-06	1.463E-12	2.183E-234
	Mean	2.119E-38	1.275E-10	8.074E-12	2.608E-03	2.454E-04	**2.352E-155**
	Standard deviation	1.050E-37	3.266E-10	2.102E-11	3.593E-03	1.256E-03	**0.000E+00**
Rosenbrock (0)	Best	**0.000E+00**	2.686E-05	4.182E-06	1.874E-03	3.530E-04	0.000E+00
	Mean	2.074E-05	6.999E-01	1.723E-03	9.227E-02	1.459E+00	**0.000E+00**
	Standard deviation	1.466E-04	2.316E+00	3.647E-03	1.079E-01	2.080E+00	**0.000E+00**
Trid (-200)	Best	**-2.100E+02**	-2.100E+02	-2.026E+02	6.203E+02	-1.126E+02	-2.100E+02
	Mean	**-2.100E+02**	-2.100E+02	-1.901E+02	2.502E+03	2.700E+02	-2.100E+02
	Standard deviation	**8.042E-10**	3.310E-02	8.723E+00	1.349E+03	2.887E+02	2.616E-02

Table 3 continued

Test Problem (Global best)		ASHEA	GA	CSA	PSO	HSA	BA
Zakharov (0)	Best	**0.000E+00**	2.576E-14	1.723E-13	5.897E-09	2.319E-12	6.778E-218
	Mean	3.351E-16	2.885E-10	3.916E-11	4.932E-03	6.611E-02	7.550E-106
	Standard deviation	2.370E-15	5.977E-10	5.827E-11	5.624E-03	2.255E-01	5.338E-105
Test Problem (Global best)		**FA**	**DE**	**ABC**	**HFPSO**	**GWOCS**	**PSOGSA**
Ackley (0)	Best	4.910E-05	8.882E-16	8.882E-16	3.952E-14	4.441E-15	7.678E-13
	Mean	3.379E-04	**8.882E-16**	8.882E-16	4.463E-12	4.441E-01	1.414E-11
	Standard deviation	1.842E-04	**0.000E+00**	0.000E+00	5.110E-12	0.000E+00	6.571E-12
Booth (0)	Best	2.507E-10	0.000E+00	2.006E-17	3.477E-29	1.848E-10	1.849E-24
	Mean	1.366E-08	**0.000E+00**	6.806E-11	6.932E-24	1.027E-06	8.710E-23
	Standard deviation	1.328E-08	**0.000E+00**	4.373E-10	3.413E-23	9.738E-07	9.516E-23
Branin (-0.397887)	Best	3.979E-01	3.979E-01	3.979E-01	3.979E-01	3.979E-01	3.979E-01
	Mean	3.983E-01	3.979E-01	3.979E-01	3.979E-01	3.979E-01	3.979E-01
	Standard deviation	3.156E-03	**3.364E-16**	9.195E-10	3.364E-16	6.076E-06	3.364E-16
Goldstein Price (-3)	Best	3.000E+00	3.000E+00	3.000E+00	3.000E+00	3.000E+00	3.000E+00
	Mean	3.000E+00	3.000E+00	3.001E+00	3.000E+00	3.000E+00	3.000E+00
	Standard deviation	5.945E-08	3.197E-15	1.354E-03	**2.001E-15**	1.147E-04	3.019E-15
Hump (0)	Best	4.655E-08	4.651E-08	4.651E-08	4.651E-08	4.711E-08	4.651E-08
	Mean	7.333E-06	4.651E-08	4.651E-08	4.651E-08	1.284E-07	4.651E-08
	Standard deviation	5.149E-05	**6.729E-17**	6.344E-17	2.067E-16	7.964E-08	8.559E-17
Matyas (0)	Best	1.630E-11	1.748E-53	1.196E-08	0.000E+00	4.296E-87	8.276E-26
	Mean	3.572E-10	5.018E-48	7.665E-05	6.740E-23	2.660E-69	3.468E-24
	Standard deviation	4.142E-10	2.521E-47	1.150E-04	2.601E-22	1.265E-68	5.079E-24
Perm (0)	Best	3.577E-14	0.000E+00	4.236E-15	0.000E+00	5.426E-10	2.484E-24
	Mean	9.313E-11	**0.000E+00**	4.505E-07	1.838E-20	7.890E-07	1.286E-22
	Standard deviation	2.045E-10	**0.000E+00**	1.698E-06	6.562E-20	1.832E-06	1.401E-22
Power Sum (0)	Best	1.691E-07	7.793E-06	8.869E-04	2.000E-06	5.923E-04	1.487E-07
	Mean	7.328E-03	4.369E-02	3.897E-02	1.587E-03	3.287E-02	2.117E-03
	Standard deviation	1.333E-02	4.832E-02	3.062E-02	3.411E-03	5.066E-02	3.432E-03
Rastrigin (0)	Best	3.762E-09	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00
	Mean	1.990E-02	0.000E+00	0.000E+00	0.000E+00	0.000E+00	5.373E-01
	Standard deviation	1.407E-01	0.000E+00	0.000E+00	0.000E+00	0.000E+00	5.760E-01
Sphere (0)	Best	1.611E-11	5.807E-15	1.822E-20	5.979E-30	1.114E-171	4.352E-25
	Mean	7.974E-10	8.074E-12	1.442E-18	1.321E-24	2.999E-137	3.334E-23
	Standard deviation	7.672E-10	2.102E-11	1.657E-18	4.930E-24	1.628E-136	3.650E-23
Rosenbrock (0)	Best	5.202E-10	0.000E+00	1.558E-05	1.476E-15	8.644E-09	1.933E-23
	Mean	4.235E-08	0.000E+00	5.419E-03	2.216E-10	2.394E-06	1.551E-02
	Standard deviation	5.252E-08	0.000E+00	5.856E-03	9.998E-10	3.031E-06	9.219E-02

Table 3 continued

Test Problem (Global best)		FA	DE	ABC	HFPSO	GWOCS	PSOGSA
Trid (-200)	Best	-2.100E+02	-2.100E+02	-2.098E+02	-2.100E+02	-2.100E+02	-2.100E+02
	Mean	-2.076E+02	-2.100E+02	-2.067E+02	-2.100E+02	-1.886E+02	-1.551E+02
	Standard deviation	3.605E+00	8.622E-03	2.936E+00	1.498E-02	3.611E+01	6.152E+01
Zakharov (0)	Best	1.242E-10	1.909E-63	2.463E-19	1.230E-29	2.854E-161	4.197E-25
	Mean	2.949E-09	2.085E-57	3.695E-18	3.844E-24	**2.204E-128**	5.850E-23
	Standard deviation	3.046E-09	1.308E-56	3.274E-18	1.324E-23	**1.544E-127**	5.595E-23

The best OF values are bolded in the appropriate rows

- The experimental setup includes a wide range of problems, incorporating the complete test suites of CEC 2011 real world optimization problems (RWOPs) and CEC 2020 real world single objective constrained optimization problems (RWSOCOPs), along with standard unconstrained problems.
- In order to ensure a comprehensive evaluation, we have conducted careful comparisons between the proposed algorithm and widely used EAs. The resulting data has been subjected to statistical analysis, providing reliable and significant insights.

The subsequent sections round up the presentation of this work. Section 2 details the proposed algorithm. The problems used and the values of the experiment parameters are reported in Section 3. Section 4 discusses the comparative analysis of ASHEA to other well-known EAs and its effectiveness. The findings are compiled in Section 5.

2. A novel proposed algorithm: ASHEA

The working of an ASHEA is explained in this section with its framework, preliminaries used and the essential constituents.

2.1 *Framework of ASHEA*

The ASHEA is represented in the form of generic diagram in figure 1. The initialization is done with the population produced at random, and corresponding objective function (OF) values are obtained. The new individuals are calculated through two main constituents of ASHEA, i.e., the global search approach and the local search approach. If a newly generated individual improves the OF value, the previous individual in the same position is supplanted by the newly formed individual. The ε-constraint method is used for constraint handling [45, 46].

The provision of replacement with a randomly generated individual is also incorporated on encountering duplicate individuals. The population is sorted from best to worst OF values just at the completion of every iteration. As the initial value of the objective function counter (*ofc*) is zero, the algorithm begins with a local search approach. Depending on the *ofc* value, the algorithm shifts between the global search approach and the local search approach. As a result, the algorithm investigates unexplored regions and exploits current promising region. The algorithm keeps running until the termination criteria are met. The pseudo code with typical notations, relevant equations and other details with greater readability is presented in figure 2. The critical hyperparameters namely, controlling factor during local search C_l, controlling factor during global search C_g, probability of variable exchange in local search P_{el} and probability of variable exchange in global search P_{eg} are

Table 4. EA-wise results for CEC 2011 RWOPs.

Problem (Dimension)		ASHEA	GA	CSA	PSO	HSA	BA
Parameter optimization for FM synthesis (D=6)	Best	**0.000E+00**	2.321E-07	1.716E+00	2.002E+01	3.382E-07	1.189E+01
	Mean	1.168E+01	1.548E+01	1.340E+01	2.566E+01	1.336E+01	1.855E+01
	SD	7.264E+00	4.935E+00	3.779E+00	**1.953E+00**	7.921E+00	4.025E+00
Lennard Jones molecular potential energy problem (D=30)	Best	**-2.465E+01**	-2.310E+01	-9.566E+00	-8.647E+00	-2.104E+01	-2.315E+01
	Mean	-1.713E+01	-1.625E+01	-6.636E+00	-5.783E+00	-1.805E+01	-1.588E+01
	SD	5.055E+00	4.910E+00	**9.054E-01**	9.697E-01	2.126E+00	5.154E+00
Optimal control problem of catalyst-blend (D=1)	Best	1.151E-05	1.151E-05	1.151E-05	1.151E-05	1.151E-05	1.151E-05
	Mean	1.151E-05	1.151E-05	1.151E-05	1.151E-05	1.151E-05	1.151E-05
	SD	2.069E-19	3.640E-12	**1.318E-19**	1.318E-19	1.318E-19	1.805E-19
CSTR optimal control problem (D=1)	Best	**1.377E+01**	1.461E+01	1.377E+01	1.386E+01	1.433E+01	1.380E+01
	Mean	**1.403E+01**	2.106E+01	1.421E+01	1.434E+01	1.996E+01	1.417E+01
	SD	2.474E-01	1.399E+00	1.076E+00	3.057E-01	2.507E+00	**2.158E-01**
Tersoff potential problem for Sc(B) (D=30)	Best	**-3.685E+01**	-3.487E+01	-3.394E+01	-1.601E+01	-1.434E+01	-3.115E+01
	Mean	-3.353E+01	-3.221E+01	-2.887E+01	-1.185E+01	-6.844E-01	-2.278E+01
	SD	2.070E+00	2.824E+00	1.730E+00	1.712E+00	3.365E+01	3.277E+00
Tersoff potential problem for Sc(C) (D=30)	Best	**-2.917E+01**	-2.743E+01	-2.654E+01	-1.113E+01	-1.434E+01	-1.941E+01
	Mean	**-2.651E+01**	-2.157E+01	-2.286E+01	-7.197E+00	-6.844E-01	-1.353E+01
	SD	3.305E+00	3.638E+00	1.284E+00	2.973E+00	3.365E+01	3.481E+00
Spread spectrum radar polyphase code problem (D=20)	Best	6.362E-01	1.009E+00	1.164E+00	1.910E+00	1.849E+00	1.009E+00
	Mean	1.114E+00	1.398E+00	1.325E+00	2.257E+00	2.264E+00	1.507E+00
	SD	2.533E-01	1.864E-01	9.310E-02	1.857E-01	1.735E-01	2.238E-01
Transmission network expansion planning problem (D=7)	Best	**3.262E+03**	6.741E+03	3.262E+03	6.140E+03	3.262E+03	3.262E+03
	Mean	**3.262E+03**	1.353E+04	3.262E+03	1.461E+04	3.305E+03	3.262E+03
	SD	**1.608E-13**	4.834E+03	5.413E-13	3.714E+03	5.586E+01	6.498E-13
Large scale transmission pricing problem (D=126)	Best	2.039E+03	8.929E+02	9.043E+04	4.507E+04	6.288E+05	4.407E+04
	Mean	1.891E+04	6.156E+03	1.254E+05	1.570E+05	7.045E+05	1.554E+05
	SD	2.545E+04	7.079E+03	1.801E+04	1.290E+05	4.314E+04	1.302E+05
Circular antenna array design problem (D=12)	Best	-2.142E+01	-1.941E+01	-1.653E+01	-1.073E+01	-1.781E+01	-1.463E+01
	Mean	-1.390E+01	-1.302E+01	-1.426E+01	-8.900E+00	-1.282E+01	-1.119E+01
	SD	3.212E+00	2.071E+00	**1.044E+00**	1.262E+00	1.530E+00	1.302E+00
DED instance 1 (D=120)	Best	**5.124E+04**	5.258E+04	5.175E+05	1.611E+08	1.191E+07	4.022E+05
	Mean	5.343E+04	5.290E+04	7.055E+05	2.997E+08	2.354E+07	9.111E+05
	SD	5.086E+03	**1.500E+02**	1.159E+05	6.267E+07	6.465E+06	2.671E+05
DED instance 2 (D=240)	Best	**1.072E+06**	1.075E+06	1.604E+06	9.854E+06	4.276E+06	1.824E+06
	Mean	1.108E+06	1.111E+06	2.084E+06	1.385E+07	4.959E+06	2.592E+06
	SD	4.032E+04	4.518E+04	2.410E+05	2.108E+06	3.267E+05	4.214E+05
ELD Instance 1 (D=6)	Best	1.544E+04	1.545E+04	1.545E+04	1.553E+04	1.545E+04	1.547E+04
	Mean	1.549E+04	1.547E+04	**1.545E+04**	1.562E+04	1.550E+04	1.552E+04
	SD	2.940E+01	1.646E+01	4.657E+00	6.468E+01	9.758E+01	3.538E+01

Table 4 continued

Problem (Dimension)		ASHEA	GA	CSA	PSO	HSA	BA
ELD Instance 2 (D=13)	Best	**1.856E+04**	1.891E+04	1.882E+04	1.875E+04	1.939E+04	1.905E+04
	Mean	1.881E+04	1.929E+04	1.897E+04	1.948E+04	3.499E+04	1.938E+04
	SD	1.640E+02	1.763E+02	**7.937E+01**	4.571E+02	2.105E+04	2.040E+02
ELD Instance 3 (D=15)	Best	**3.282E+04**	3.297E+04	3.283E+04	3.283E+04	3.301E+04	3.286E+04
	Mean	**3.300E+04**	3.312E+04	3.296E+04	3.310E+04	3.322E+04	4.258E+04
	SD	1.282E+02	9.114E+01	4.837E+01	1.362E+02	7.832E+01	2.463E+04
ELD Instance 4 (D=40)	Best	**1.306E+05**	1.306E+05	1.314E+05	1.307E+05	1.475E+05	1.343E+05
	Mean	1.405E+05	1.432E+05	1.366E+05	1.437E+05	1.794E+05	1.440E+05
	SD	6.202E+03	5.528E+03	2.797E+03	8.005E+03	3.203E+04	6.812E+03
ELD Instance 5 (D=140)	Best	**1.913E+06**	1.959E+06	4.722E+06	9.379E+08	1.153E+07	2.017E+06
	Mean	**2.114E+06**	3.109E+08	5.661E+09	4.739E+09	3.802E+08	2.960E+08
	SD	**2.980E+05**	3.371E+08	4.456E+09	1.931E+09	3.108E+08	4.986E+08
Hydrothermal scheduling instance 1 (D=96)	Best	**9.424E+05**	9.425E+05	9.764E+05	1.352E+06	7.095E+06	9.634E+05
	Mean	**9.787E+05**	1.613E+06	1.071E+06	9.008E+06	1.111E+07	1.419E+06
	SD	8.996E+04	8.058E+05	**7.848E+04**	1.173E+07	2.337E+06	6.785E+05
Hydrothermal scheduling instance 2 (D=96)	Best	9.479E+05	1.424E+06	1.332E+06	1.358E+06	3.831E+06	1.342E+06
	Mean	1.153E+06	2.215E+06	1.587E+06	8.016E+06	1.120E+07	2.021E+06
	SD	3.163E+05	8.150E+05	1.456E+05	1.159E+07	3.253E+06	6.195E+05
Hydrothermal scheduling instance 3 (D=96)	Best	9.452E+05	9.425E+05	9.764E+05	1.352E+06	7.095E+06	9.634E+05
	Mean	1.046E+06	1.613E+06	1.071E+06	9.008E+06	1.111E+07	1.419E+06
	SD	2.970E+05	8.058E+05	7.848E+04	1.173E+07	2.337E+06	6.785E+05
Messenger: Spacecraft trajectory optimization problem (D=26)	Best	**1.167E+01**	1.251E+01	2.267E+01	6.148E+01	1.803E+01	1.854E+01
	Mean	**1.873E+01**	1.929E+01	2.698E+01	9.753E+01	3.737E+01	3.488E+01
	SD	3.422E+00	4.394E+00	**2.130E+00**	3.305E+01	8.174E+00	7.765E+00
Cassini 2: Spacecraft trajectory optimization problem (D=22)	Best	1.249E+01	1.495E+01	2.361E+01	3.978E+01	2.514E+01	2.211E+01
	Mean	2.059E+01	2.395E+01	2.785E+01	5.160E+01	3.341E+01	3.346E+01
	SD	4.287E+00	3.880E+00	**2.305E+00**	1.221E+01	5.637E+00	7.510E+00

Problem (Dimension)		FA	DE	ABC	HFPSO	GWOCS	PSOGSA
Parameter optimization for FM synthesis (D=6)	Best	7.578E-05	**0.000E+00**	7.407E-01	1.495E-26	1.054E+01	9.693E+00
	Mean	1.665E+01	**6.115E+00**	9.037E+00	1.701E+01	1.798E+01	2.095E+01
	SD	5.564E+00	7.329E+00	4.754E+00	6.811E+00	5.952E+00	4.389E+00
Lennard Jones molecular potential energy problem (D=30)	Best	-1.695E+01	-2.093E+01	-2.036E+01	-2.324E+01	-2.373E+01	-2.203E+01
	Mean	-1.208E+01	-1.022E+01	-1.698E+01	-1.979E+01	**-2.151E+01**	-1.010E+01
	SD	2.595E+00	3.636E+00	1.874E+00	3.409E+00	1.473E+00	3.764E+00
Optimal control problem of catalyst-blend (D=1)	Best	1.151E-05	1.151E-05	1.151E-05	**1.151E-05**	1.151E-05	1.151E-05
	Mean	1.151E-05	1.151E-05	1.151E-05	**1.151E-05**	1.151E-05	1.151E-05
	SD	9.714E-19	3.975E-19	5.343E-19	1.594E-19	1.318E-19	1.418E-19
CSTR optimal control problem (D=1)	Best	1.395E+01	1.377E+01	1.395E+01	1.433E+01	1.379E+01	1.481E+01
	Mean	1.483E+01	1.888E+01	1.454E+01	1.725E+01	1.406E+01	2.083E+01
	SD	1.014E+00	2.959E+00	4.152E-01	3.358E+00	2.251E-01	1.854E+00

Table 4 continued

Problem (Dimension)		FA	DE	ABC	HFPSO	GWOCS	PSOGSA
Tersoff potential problem for Sc(B) (D=30)	Best	-1.347E+01	-1.628E+01	-3.682E+01	-3.416E+01	-3.444E+01	-1.285E+01
	Mean	2.813E+01	-1.417E+01	**-3.409E+01**	-2.854E+01	-3.066E+01	-6.020E+00
	SD	1.628E+02	1.525E+00	**-6.758E+00**	4.608E+00	2.695E+00	6.648E+00
Tersoff potential problem for Sc(C) (D=30)	Best	-7.117E-01	-7.069E+00	-6.758E+00	-2.034E+01	-2.917E+01	5.636E-01
	Mean	1.038E+02	3.703E+00	4.915E+00	-1.742E+01	-2.297E+01	9.588E-01
	SD	9.773E+01	1.590E+01	1.509E+01	2.673E+00	3.315E+00	**1.680E-01**
Spread spectrum radar polyphase code problem (D=20)	Best	5.551E-01	1.550E+00	1.187E+00	6.601E-01	**5.099E-01**	3.262E+03
	Mean	**9.190E-01**	1.876E+00	1.358E+00	9.728E-01	9.979E-01	3.262E+03
	SD	1.568E-01	1.385E-01	8.367E-02	1.821E-01	3.918E-01	**1.313E-13**
Transmission network expansion planning problem (D=7)	Best	3.351E+03	3.262E+03	3.262E+03	3.262E+03	3.262E+03	1.325E+05
	Mean	5.380E+03	3.262E+03	3.262E+03	3.262E+03	3.262E+03	1.532E+05
	SD	8.120E+02	5.168E-13	1.856E-13	7.498E-13	1.148E-12	7.548E+03
Large scale transmission pricing problem (D=126)	Best	3.701E+05	2.594E+04	1.387E+03	1.127E+05	9.769E+03	**-2.157E+01**
	Mean	5.370E+05	3.770E+04	3.744E+03	2.842E+05	1.588E+04	**-1.300E+01**
	SD	9.358E+04	7.040E+03	1.348E+03	1.123E+05	4.726E+03	**2.838E+00**
Circular antenna array design problem (D=12)	Best	-2.133E+01	**-2.182E+01**	-1.937E+01	-2.177E+01	-2.132E+01	5.791E+05
	Mean	**-2.023E+01**	-1.321E+01	-1.664E+01	-1.674E+01	-1.623E+01	1.235E+06
	SD	1.554E+00	2.937E+00	1.272E+00	4.458E+00	4.980E+00	4.233E+05
DED instance 1 (D=120)	Best	5.154E+04	2.214E+05	5.223E+04	5.154E+04	5.643E+04	1.560E+06
	Mean	5.312E+04	7.977E+05	5.287E+04	**5.224E+04**	9.234E+04	2.429E+06
	SD	1.697E+03	3.475E+05	4.613E+02	6.024E+02	3.273E+04	3.453E+05
DED instance 2 (D=240)	Best	1.073E+06	1.141E+06	1.085E+06	1.082E+06	1.101E+06	1.560E+06
	Mean	**1.075E+06**	1.215E+06	1.133E+06	1.100E+06	1.171E+06	2.429E+06
	SD	**1.621E+03**	5.045E+04	3.161E+04	3.056E+04	4.303E+04	3.453E+05
ELD Instance 1 (D=6)	Best	1.547E+04	**1.544E+04**	1.545E+04	1.547E+04	1.545E+04	1.545E+04
	Mean	1.549E+04	1.546E+04	1.546E+04	1.550E+04	1.547E+04	1.549E+04
	SD	8.390E+00	1.500E+01	**4.428E+00**	2.577E+01	1.609E+01	3.888E+01
ELD Instance 2 (D=13)	Best	1.904E+04	1.860E+04	1.865E+04	1.897E+04	1.889E+04	1.894E+04
	Mean	1.930E+04	**1.879E+04**	1.899E+04	1.922E+04	1.937E+04	6.365E+04
	SD	1.749E+02	9.654E+01	1.422E+02	1.688E+02	1.994E+02	7.638E+04
ELD Instance 3 (D=15)	Best	3.298E+04	3.281E+04	3.294E+04	3.282E+04	3.307E+04	3.301E+04
	Mean	3.313E+04	3.291E+04	3.301E+04	3.307E+04	3.315E+04	3.323E+04
	SD	6.892E+01	5.686E+01	**4.164E+01**	1.227E+02	5.979E+01	1.091E+02
ELD Instance 4 (D=40)	Best	1.344E+05	1.324E+05	1.324E+05	1.324E+05	1.353E+05	3.773E+05
	Mean	1.422E+05	1.396E+05	**1.359E+05**	1.459E+05	1.436E+05	1.497E+06
	SD	3.731E+03	3.854E+03	**1.833E+03**	6.553E+03	4.574E+03	6.412E+05
ELD Instance 5 (D=140)	Best	1.941E+06	1.996E+06	1.915E+06	1.922E+06	1.974E+06	1.919E+06
	Mean	2.387E+06	3.032E+06	2.268E+06	1.116E+07	3.259E+06	2.406E+06
	SD	4.977E+05	6.125E+05	3.713E+05	2.637E+07	7.275E+05	6.426E+05

t-
a-

Table 4 continued

Problem (Dimension)		FA	DE	ABC	HFPSO	GWOCS	PSOGSA
Hydrothermal scheduling instance 1 (D=96)	Best	9.430E+05	1.836E+06	1.726E+07	9.465E+05	9.589E+05	4.601E+06
	Mean	9.912E+05	2.395E+06	2.328E+07	1.090E+06	1.025E+06	7.998E+06
	SD	9.219E+04	3.697E+05	1.984E+06	3.603E+05	1.140E+05	2.065E+06
Hydrothermal scheduling instance 2 (D=96)	Best	**3.701E+05**	2.425E+06	1.372E+07	1.012E+06	1.217E+06	5.578E+06
	Mean	**5.370E+05**	3.260E+06	2.087E+07	1.367E+06	1.585E+06	7.966E+06
	SD	**9.358E+04**	4.712E+05	2.602E+06	4.917E+05	2.328E+05	1.822E+06
Hydrothermal scheduling instance 3 (D=96)	Best	**9.419E+05**	1.836E+06	1.726E+07	9.462E+05	9.589E+05	4.601E+06
	Mean	**9.823E+05**	2.395E+06	2.328E+07	1.302E+06	1.025E+06	7.998E+06
	SD	**7.752E+04**	3.697E+05	1.984E+06	6.262E+05	1.140E+05	2.065E+06
Messenger: Spacecraft trajectory optimization problem (D=26)	Best	1.599E+01	1.582E+01	1.527E+01	1.321E+01	1.446E+01	8.603E+01
	Mean	1.948E+01	2.121E+01	2.084E+01	1.952E+01	2.188E+01	1.199E+02
	SD	2.684E+00	3.346E+00	2.922E+00	3.948E+00	4.966E+00	1.848E+01
Cassini 2: Spacecraft trajectory optimization problem (D=22)	Best	1.837E+01	**1.173E+01**	1.226E+01	1.890E+01	1.895E+01	6.765E+01
	Mean	2.437E+01	**1.592E+01**	2.211E+01	2.376E+01	2.448E+01	9.317E+01
	SD	2.853E+00	3.057E+00	3.937E+00	3.506E+00	2.621E+00	1.258E+01

The best OF values are bolded in the appropriate rows

ken as 1.5, 2, 0.05 and 0.3 respectively as a result of sensitivity study.

Below is a concise overview of the DE, CSA and FA, which became helpful for global and local search approaches of ASHEA. The details of these algorithms can be found in the respective cited literature.

2.1.1 *DE* A stochastic, bio-inspired, and evolution-based DE algorithm has proven to be one of the preferred algorithms for addressing optimization problems and has gained widespread acceptance [47, 48]. This algorithm was established in 1997 and is an improved counterpart of genetic algorithms [18]. With mutation, crossover, and selection processes as constituents, DE leverages individuals' differences to generate new offspring to drive the algorithm in the next iteration. A mutant vector is formed from the parent population by multiplying the differential term of two randomly chosen individuals by the scale factor. Inspired by the six popular mutation strategies, the following mutation strategies are used in the current study.

$$x_i^{t+1} = x_i^t + S_{f1}(x_{r2} - x_{r3}) \quad (1)$$

$$x_i^{t+1} = x_{r1} + S_{f2}(x_{r2} - x_{r3}) + (1 - S_{f2})(x_{r4} - x_{r5}) \quad (2)$$

$$x_i^{t+1} = x_i^t + S_{f2}(x_{best} - x_i^t) + (1 - S_{f2})(x_{r2} - x_0) \quad (3)$$

$$x_i^{t+1} = x_{best} + rand(x_{r1} - x_i^t) + (1 - S_{f2})(x_{r2} - x_{r3}) \quad (4)$$

where x_{r1}, x_{r2}, x_{r3}, x_{r4} and x_{r5} are distinct individuals drawn at random from the parent population and scale factor, S_{f1} and S_{f2} are scalar numbers. The above equations are improved variants of the DE/rand/1, DE/rand/2, DE/current-to-best/1, and DE/current-to-rand/1 mutation techniques. These strategies are employed in conjunction with the following improvisations in this instance.

For DE/rand/1, the difference x_i^t is the current solution rather than a random individual. In contrast to DE/current-to-best/1, x_0 represents a random individual from the archive pool instead of a random individual from the current population. The rejected individuals are included to the archive pool. Newly rejected individuals replace older individuals when the archive pool size exceeds a preset value. For DE/current-to-rand/1, the difference is that the target individual is x_{best} rather than x_i^t. Furthermore, the scale factor of the second term for DE/rand/2, DE/current-to-best/1, and DE/current-to-rand/1 is $(1 - S_{f2})$ rather than S_{f2}.

2.1.2 *CSA* Originating from the inspiration of breeding strategies of certain cuckoo species in nature, CSA is one of the popular metaheuristic algorithms [49]. Yang and Deb created this algorithm with fewer parameters and it is straight forward [19]. The CSA includes Levy flights, which provide a distribution of mostly small step lengths

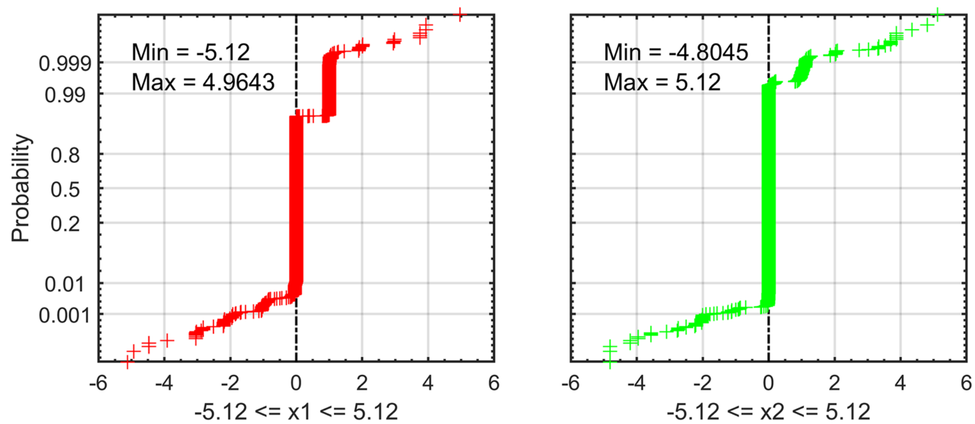

Figure 3. Rastrigin function search space exploration of ASHEA.

and occasionally large step lengths with random directions. The following equation obtains the updating of an individual for the *t+1* *th* iteration,

$$x_i^{t+1} = x_i^t + \alpha \oplus Levy(\lambda) \tag{5}$$

$$where, \alpha = \alpha_0 (x_i^t - x_{best})$$

$$Levy(\lambda) = \frac{u}{|v|^{\frac{1}{\beta}}}, u \in (0, \delta_u^2),\ v \in (0,1)$$

$$\delta_u = \left\{ \frac{\Gamma(\lambda) \sin\left(\frac{\pi(\lambda-1)}{2}\right)}{\Gamma\left(\frac{\lambda}{2}\right)(\lambda-1) \times 2^{\left(\frac{\lambda}{2}\right)}} \right\}^{\frac{1}{(\lambda-1)}},\ 1 \le \beta \le 2$$

Here, α is a scale factor with a usual value of $\alpha_0 = 0.01$, $\oplus$ indicates element-wise multiplication and $Levy(\lambda)$ represents Levy random steps distribution. With influence from CSA, the present study updates an individual for the *t+1* *th* iteration as follows.

$$x_i^{t+1} = x_i^t + M(x_i^t - x_{best}) \tag{6}$$

$$where,\ M = randn \frac{|randn|^{\beta_2}}{randn}$$

The *randn* is a pseudorandom number generated by the standard normal distribution, andβ_2 is a pseudorandomly chosen integer number using the discrete uniform distribution over the range *[1,4]*.

2.1.3 *FA* The FA comes from the bioluminescent communication abilities of fireflies while flying to each other in the dark [21]. The attractiveness of fireflies, which shows their relative brightness, represents their OF values for a given problem. The following Euclidean distance equation is used to compute the distance between fireflies *i* and *j* in a *D* dimensional problem.

$$r_{ij} = \sqrt{\sum_{k=1}^{D} (x_{ik} - x_{jk})^2}$$

The updated movement of the attracted firefly *i* in the direction of the brighter firefly *j* is calculated as,

$$x_i^{t+1} = x_i^t + \sigma(x_j^t - x_i^t) + \phi \varepsilon_i \tag{7}$$

where $\sigma = \sigma_0 e^{-\gamma r_{ij}^2}$ is attractiveness, $\phi \in [0,1]$ and $\varepsilon_i \in [-0.5, 0.5]$. From the inspiration from FA, the equation of movement updating is improvised in the present study as,

$$x_i^{t+1} = x_i^t + \sigma(x_j^t - x_i^t) + \psi \tag{8}$$

$$where,\ Shift\ factor,\ \psi = (1-\mu) S_i b_s$$

$$\mu = \frac{iter}{\max iter}, S_i \in [-0.5, 0.5],\ \text{and}\ b_s = |x_{\max} - x_{\min}|$$

2.2 *Global search approach*

This sub-section discusses the functioning of the adopted global search scheme. The global search of the ASHEA is executed by the algorithm when the local search outputs for improved results become stagnant. The following equations with a random probability of standard uniform distribution are used to generate new offspring for the next iteration.

$$x_i^{t+1} = x_i^t + M(x_i^t - x_{best}) \tag{9}$$

$$x_i^{t+1} = x_i^t + S_{f1}(x_{r2,g} - x_{r3,g}) \tag{10}$$

$$x_i^{t+1} = x_{best} + S_{f2}(x_i^t - x_{r3,g}) + (1 - S_{f2})(x_{r1,g} - x_{r2,g}) \tag{11}$$

The CSA is used here to get the benefits of Levy flight's exploration. For a given problem of dimension, *D,* and population size as *n*, the $x_{r1,g}$, $x_{r2,g}$ and $x_{r3,g}$ are randomly

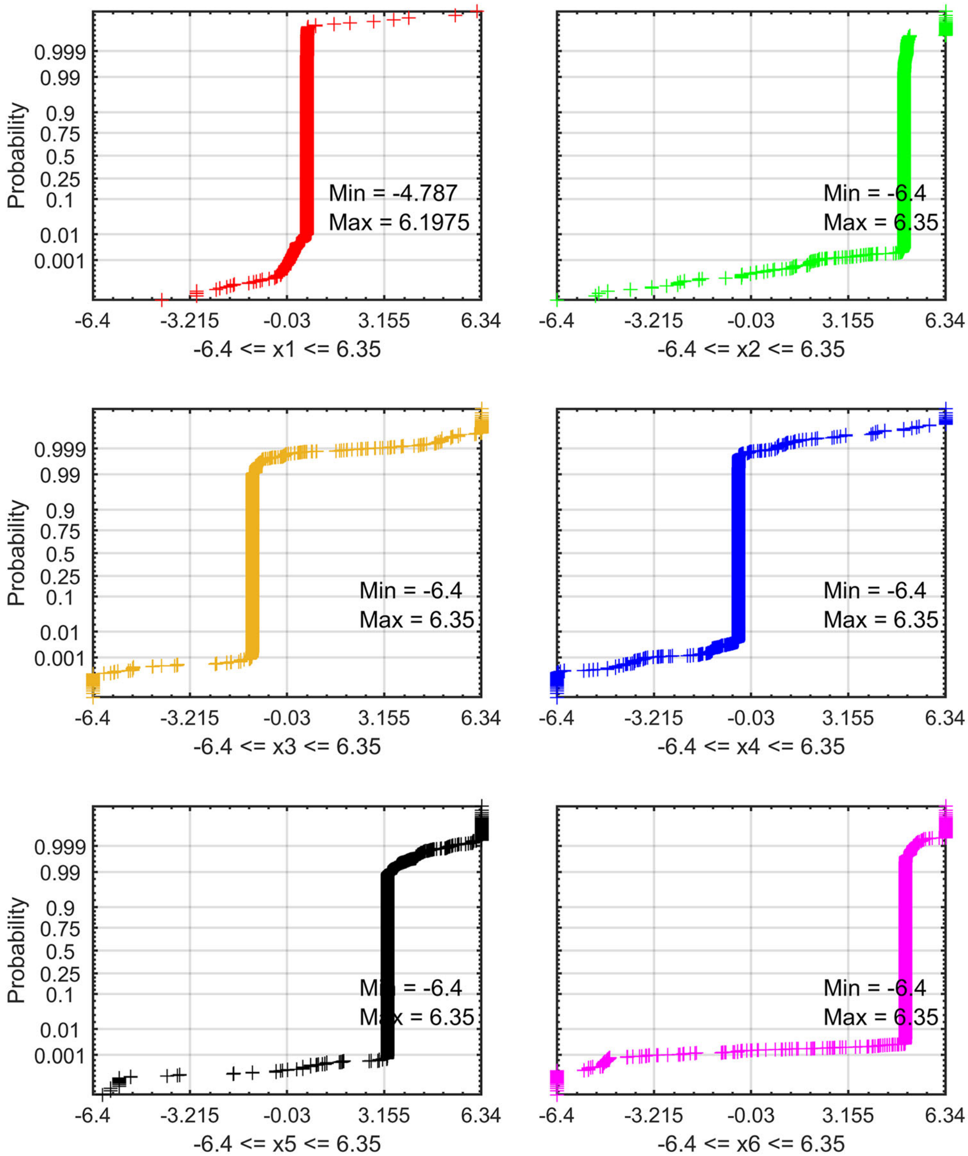

Figure 4. *Parameter optimization for frequency modulation synthesis* CEC 2011 function search space exploration of ASHEA.

selected elements (between *1* and *D*) of randomly selected individuals (between *1* and *n*). In other words, for a current i^{th} element under consideration, the $x_{r1,g}$, $x_{r2,g}$ and $x_{r3,g}$ are chosen randomly from entire *n* by *D* matrix. This high randomness explores the search space effectively. In addition, the variable exchange is conducted before OF value calculation for the current iteration. This exchange is done with a probability of continuous random value generated by the uniform distribution over the range *[0.1,0.3]*.

2.3 *Local search approach*

In conjunction with the adopted individual upgradation strategies, the local search seeks to find the improved solution within sub-regions. Here, the i) DE mutation techniques DE/rand/2, DE/current-to-best/1, and DE/current-to-rand/1 (as shown in (2), (3), and (4)); ii) the CSA with random walk given by *M*, and; iii) firefly movement of FA for fireflies' brightness difference together constitutes the local search approach (refer figure 2). Here, the mutation scheme uses the elements from the randomly picked individual from a given population. It should be noted here that the DE mutation scheme is different from that used in the global search approach. Here, for the i^{th} element under consideration, the x_{r1}, x_{r2}, x_{r3}, x_{r4} and x_{r5} are selected from the same column only, but not from the entire *n* by *D* matrix. The archive pool is found to be helpful sometimes to achieve better results. The local search also incorporates an archive pool to take this advantage in the DE/current-to-

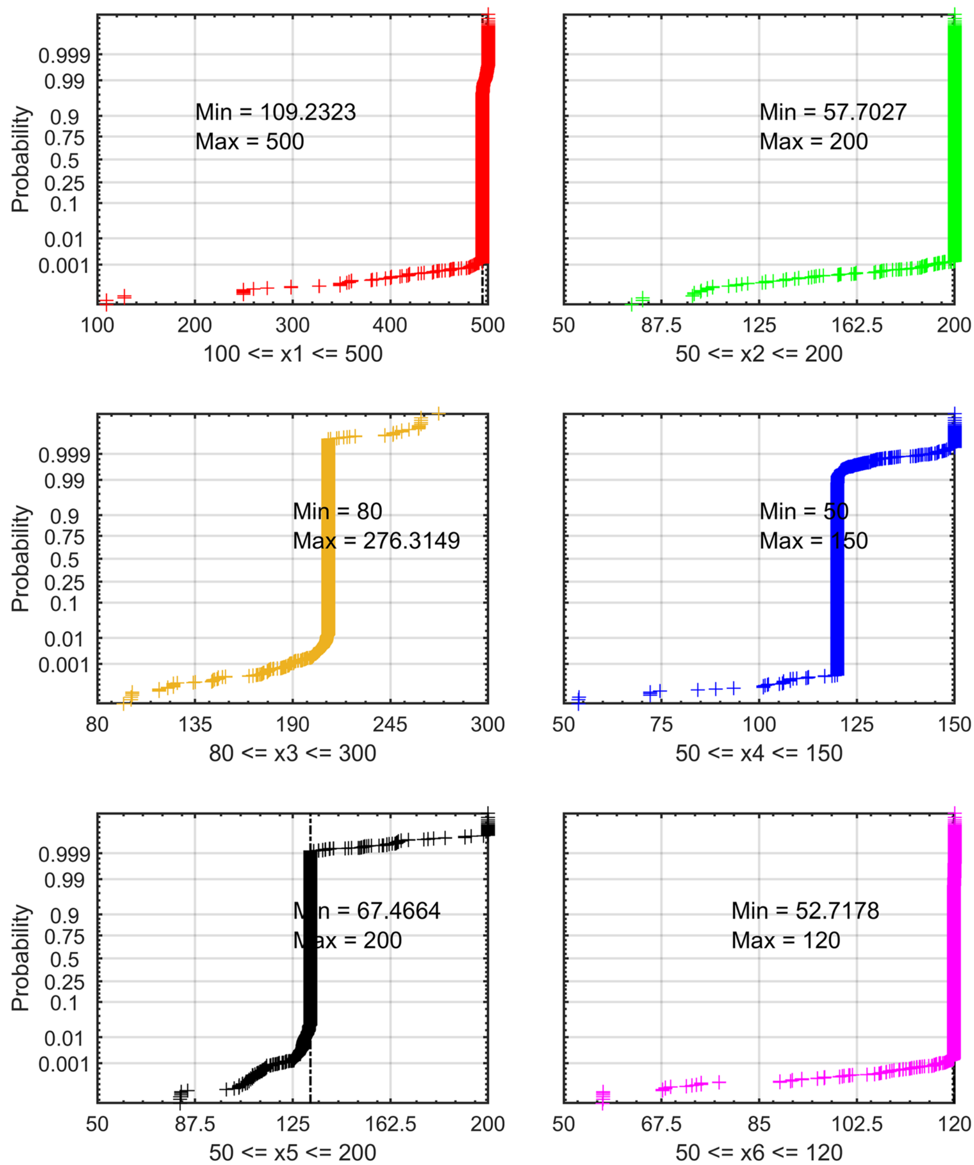

Figure 5. *Static economic load dispatch problem (ELD instance 1)* CEC 2011 function search space exploration of ASHEA.

best/1 mutation scheme. The newly found best solution replaces the current best solution if it is found to be an improved one. When the local search approach becomes static in getting improved solutions, it shifts to the global search approach.

3. Experimental setup

The performance of ASHEA is checked through its comparisons with well-established EAs and three hybrid algorithms. An ample amount of standard unconstrained optimization problems and high dimensional CEC 2011 RWOPs (with CEC guidelines confirmation) are used to solve this purpose. To investigate the effectiveness of ASHEA, CEC 2020 RWSOCOPs are also embedded. The comprehensive information on these problems is available in [50–52]. A total of 92 optimization problems of varied sizes and complexities are explored in experiments. Standard test functions, industrial chemical processes, process synthesis and design, livestock feed ration optimization, and engineering problems are all included in this category of problems.

The S_{f1} gives a mean of 0.7 and a standard deviation (SD) of 0.1 using normal distribution in DE/rand/1 scheme of global search. The DE/rand/2, DE/current-to-best/1, and DE/best current-to-rand mutation schemes of DE uses S_{f2} in local search. The S_{f2} gives normal distribution with 0.5 mean and 0.2 SD values. The study takes a population size of 30 into account throughout. The CEC

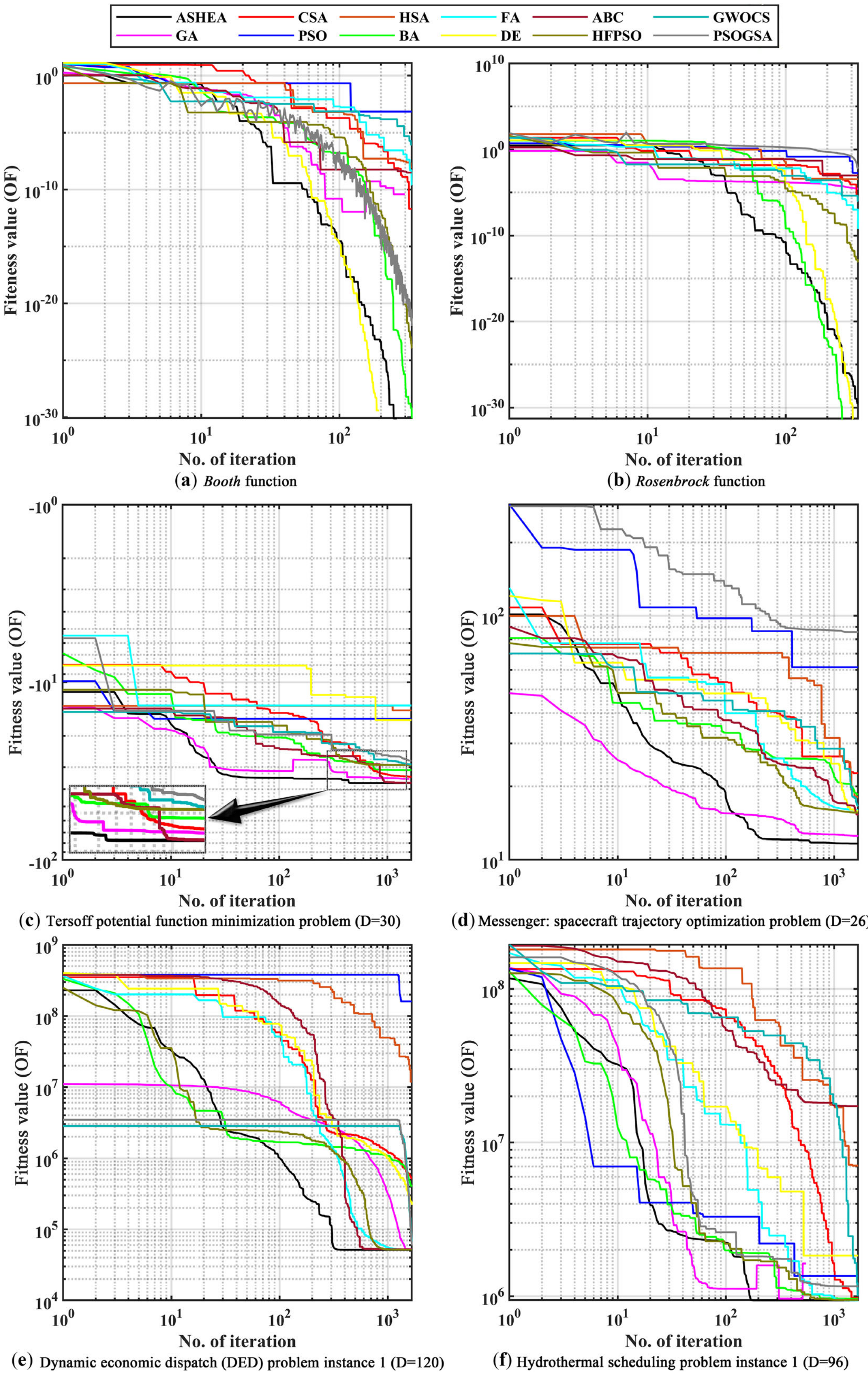

Figure 6. Convergence rates of twelve algorithms.

Table 5. Results of Friedman's test on ELD instance 5 problem.

(a)
Ranks

	Mean rank
ASHEA	2.52
GA	6.24
CSA	6.32
PSO	8.56
HSA	5.8
BA	3.76
FA	6.84
DE	3.6
ABC	1.36

(b)

	Test Statistics
N	25
Chi-Square	142.923
df	8
Asymp. Sig.	0

competition problems are subjected to 25 individual runs as per CEC guidelines, while other problems are subjected to 50 individual runs [50].

4. Results and discussion

GA, DE, ABC, CSA, BA, FA, PSO, and HSA are well-known EAs used to solve optimization problems. These EAs are chosen to cover all the categories of algorithm classification. These categories include bio-inspired algorithms based on evolution (GA and DE), bio-inspired algorithms based on swarm intelligence (ABC, CSA, BA, FA, and PSO), and music phenomena physics and chemistry based algorithms (HSA). Further, these EAs gain more attention in the optimization domain with their remarkable results. That is why these EAs are selected to investigate the performance of ASHEA through results comparisons. Additionally, HFPSO, GWOCS and PSOGSA hybrid algorithms are also considered as well in order to validate the results on versatile evolutionary computational platform. The parameterization of these EAs along with hybrid algorithms is provided in Table 2. The parameters of these EAs are chosen based on recommendations from their inventors or from literature where their values produce beneficial results [20, 53–55]. The sensitivity analysis is also carried out to verify the parameter selections.

4.1 *Comparison of ASHEA with well known EAs*

Table 3 and Table 4 summarize the comparison of ASHEA with chosen well-known EAs and three hybridized algorithms, namely HFPSO, GWOCS and PSOGSA on standard unconstrained problems and a comprehensive test suite of CEC 2011 RWOPs, respectively.

In Table 3, the numeral numbers in brackets next to the function name represent the global minimum values of the relevant test functions. In all unconstrained problems, the ASHEA finds superior solutions. In Table 4, the brackets next to the problem name in CEC 2011 RWOPs indicate the dimensions of the corresponding problems. As seen in Table 4, the ASHEA excels in 14 of the 22 CEC 2011 RWOPs. The ASHEA outperforms all other EAs regarding

Table 6. Results of Wilcoxon's test on ELD instance 5 problem.

Pair	Test statistic number	p-value	Pair	Test statistic number	p-value
ASHEA - GA	2	0.000	CSA - FA	99	0.088
ASHEA - CSA	16	0.000	CSA - DE	46	0.002
ASHEA - PSO	0	0.000	CSA - ABC	1	0.000
ASHEA - HSA	0	0.000	PSO - HSA	0	0.000
ASHEA - BA	58	0.005	PSO - BA	0	0.000
ASHEA - FA	0	0.000	PSO - FA	0	0.000
ASHEA - DE	81	0.028	PSO - DE	0	0.000
ASHEA - ABC	20	0.000	PSO - ABC	0	0.000
GA - CSA	85	0.037	HSA - BA	86	0.040
GA - PSO	0	0.000	HSA - FA	23	0.000
GA - HSA	49	0.002	HSA - DE	0	0.000
GA - BA	26	0.000	HSA - ABC	0	0.000
GA - FA	84	0.035	BA - FA	6	0.000
GA - DE	2	0.000	BA - DE	95	0.069
GA - ABC	0	0.000	BA - ABC	18	0.000
CSA - PSO	135	0.459	FA - DE	3	0.000
CSA - HSA	69	0.012	FA - ABC	0	0.000
CSA - BA	49	0.002	DE - ABC	0	0.000

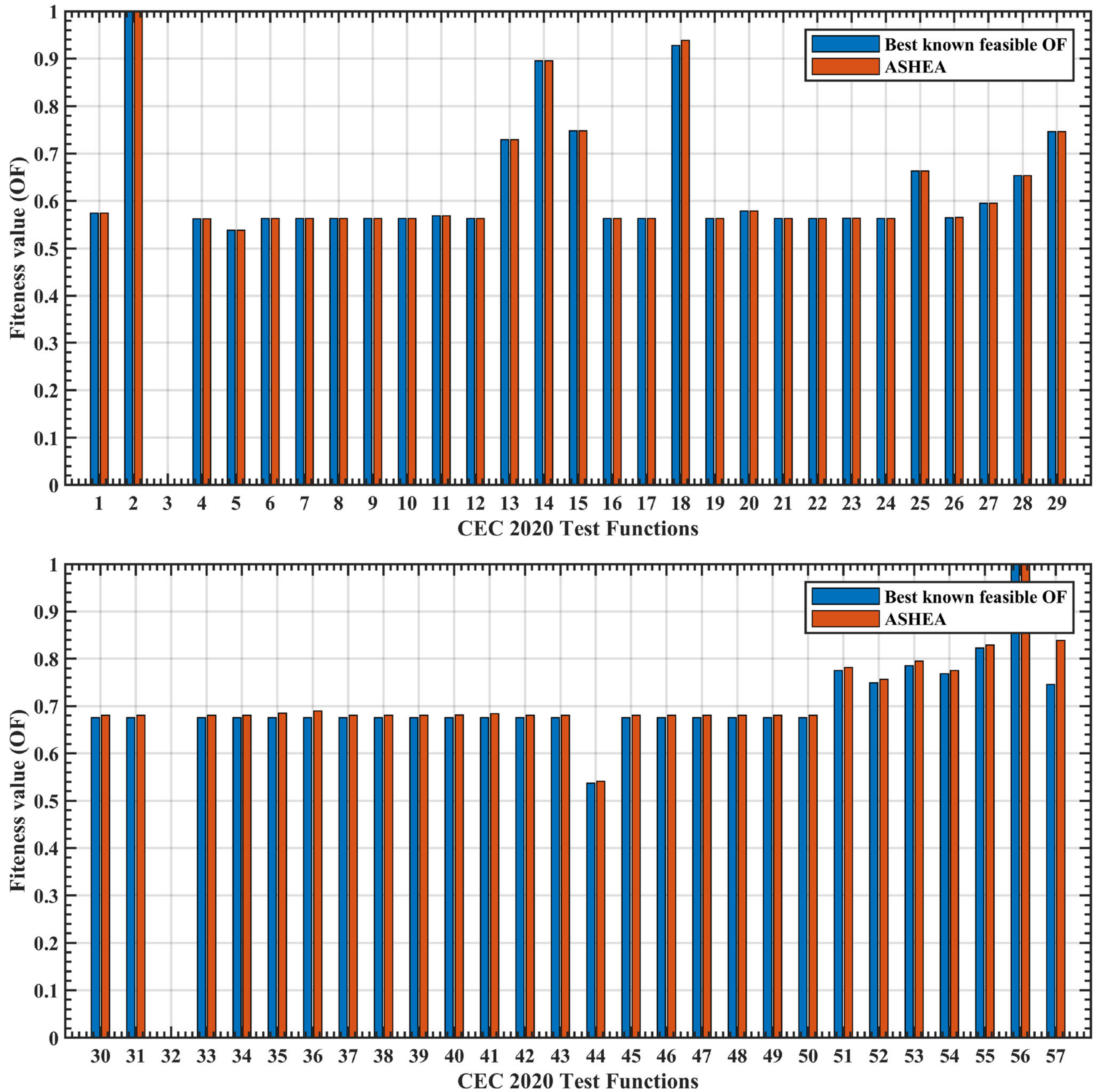

Figure 7. ASHEA simulation results for CEC 2020 RWSOCOPs.

OF value, particularly in high dimensional problems (i.e., problems 11, 12, and 17). For other problems, the ASHEA yields result that are pretty near to the best OF values.

To examine the search space exploration of ASHEA, the search space plots of typical optimization problems are collected. Figure 3 shows the plots of the search space exploration for the highly multimodal *Rastrigin* function. Two functions from CEC 2011 RWOPs, namely, Parameter optimization for FM synthesis and Static economic load dispatch problem (ELD instance 1) are also considered for search space exploration. These plots are shown in figure 4 and figure 5 respectively. The plots exhibits that the ASHEA encompasses the entirety of the search space. The concentrated portion of the line implies a higher probability of generating variables. These values are found to be in agreement with the optimum value of respective decision variables. This demonstrates the efficacy of the used local and global search approaches with improved OF values. Only three functions are considered here among remaining functions with diversity of dimension in order to manage

Table 7. ASHEA results of CEC 2020 RWSOCOPs.

Problem (Dimension)	best known feasible OF value	ASHEA OF value	ASHEA$v(x)$ value
Industrial chemical processes			
Heat Exchanger Network Design (case 1) (D=9)	1.893E+02	1.893E+02	0.000E+00
Heat Exchanger Network Design (case 2) (D=11)	7.049E+03	7.049E+03	0.000E+00
Optimal Operation of Alkylation Unit (D=7)	-4.529E+03	-4.529E+03	0.000E+00
Reactor Network Design (RND) (D=6)	-3.883E-01	-3.883E-01	0.000E+00
Haverly's Pooling Problem (D=9)	-4.000E+02	-4.000E+02	0.000E+00
Blending-Pooling-Separation problem (D=38)	1.864E+00	1.974E+00	2.188E-02
Propane, Isobutane, n-Butane Nonsharp Separation (D=48)	1.567E+00	1.890E+00	3.960E-02
Problems of process synthesis and design			
Process synthesis problem (D=2)	2.000E+00	2.000E+00	0.000E+00
Process synthesis and design problem (D=3)	2.558E+00	2.558E+00	0.000E+00
Process flow sheeting problem (D=3)	1.077E+00	1.077E+00	0.000E+00
Two-reactor Problem (D=7)	9.924E+01	9.924E+01	0.000E+00
Process synthesis problem (D=7)	2.925E+00	2.925E+00	0.000E+00
Process design Problem (D=5)	2.689E+04	2.689E+04	0.000E+00
Multi-product batch plant (D=10)	5.364E+04	5.364E+04	0.000E+00
Problems of mechanical engineering			
Weight Minimization of a Speed Reducer (D=7)	2.994E+03	2.994E+03	0.000E+00
Optimal Design of Industrial refrigeration System (D=14)	3.221E-02	3.221E-02	0.000E+00
Tension/compression spring design (case 1) (D=3)	1.267E-02	1.267E-02	0.000E+00
Pressure vessel design (D=4)	5.885E+03	6.060E+03	0.000E+00
Welded beam design (D=4)	1.670E+00	1.670E+00	0.000E+00
Three bar truss design problem (D=2)	2.639E+02	2.639E+02	0.000E+00
Multiple disk clutch brake design problem (D=5)	2.352E-01	2.352E-01	0.000E+00
Planetary gear train design optimization problem (D=9)	5.258E-01	5.258E-01	0.000E+00
Step-cone pulley problem (D=5)	1.607E+01	1.607E+01	0.000E+00
Robot gripper problem (D=7)	2.529E+00	2.529E+00	0.000E+00
Hydrostatic thrust bearing design problem (D=4)	1.616E+03	1.616E+03	0.000E+00
Four-stage gear box problem (D=22)	3.536E+01	3.644E+01	0.000E+00
10-bar truss design (D=10)	5.245E+02	5.245E+02	0.000E+00
Rolling element bearing (D=10)	1.461E+04	1.461E+04	0.000E+00
Gas Transmission Compressor Design (GTCD) (D=4)	2.965E+06	2.965E+06	0.000E+00
Tension/compression spring design (case 2) (D=3)	2.614E+00	2.659E+00	0.000E+00
Gear train design Problem (D=4)	0.000E+00	0.000E+00	0.000E+00
Himmelblau's Function (D=5)	-3.067E+04	-3.067E+04	0.000E+00
Topology Optimization (D=30)	2.639E+00	2.639E+00	0.000E+00
Problems of power system			
Optimal Sizing of Single Phase Distributed Generation with reactive power support for Phase Balancing at Main Transformer/Grid (D=118)	0.000E+00	1.700E+01	5.965E-02
Optimal Sizing of Distributed Generation for Active Power Loss Minimization (D=153)	7.996E-02	1.978E+02	7.277E-01
Optimal Sizing of Distributed Generation (DG) and Capacitors for Reactive Power Loss Minimization (D=158)	4.773E-02	4.236E+02	3.623E-01
Optimal Power flow (Minimization of Active Power Loss) (D=126)	1.859E-02	5.804E+00	7.221E-02
Optimal Power flow (Minimization of Fuel Cost) (D=126)	2.714E+00	7.666E+00	9.429E-02
Optimal Power flow (Minimization of Active Power Loss and Fuel Cost) (D=126)	2.752E+00	9.341E+00	8.552E-02
Microgrid Power flow (Islanded case) (D=76)	0.000E+00	4.357E+01	1.966E+00
Microgrid Power flow (Grid-connected case) (D=74)	0.000E+00	1.653E+02	3.343E+00
Optimal Setting of Droop Controller for Minimization of Active Power Loss in Islanded Microgrids (D=86)	7.703E-02	-1.405E+00	2.336E+00
Optimal Setting of Droop Controller for Minimization of Reactive Power Loss in Islanded Microgrids (D=86)	7.984E-02	1.694E+01	2.187E+00
Wind Farm Layout Problem (D=30)	-6.273E+03	-6.283E+03	0.000E+00
Problems of power electronic			
SOPWM for 3-level Inverters (D=25)	3.074E-02	1.078E-01	0.000E+00
SOPWM for 5-level Inverters (D=25)	2.024E-02	5.475E-02	0.000E+00

Table 7 continued

Problem (Dimension)	best known feasible OF value	ASHEA OF value	ASHEA*v(x)* value
SOPWM for 7-level Inverters (D=25)	1.278E-02	3.362E-02	0.000E+00
SOPWM for 9-level Inverters (D=30)	1.679E-02	7.591E-02	0.000E+00
SOPWM for 11-level Inverters (D=30)	9.312E-03	7.958E-02	0.000E+00
SOPWM for 13-level Inverters (D=30)	1.505E-02	2.992E-01	2.671E-03
Livestock feed ration optimization			
Beef Cattle(case 1) (D=59)	4.551E+03	4.551E+03	3.114E-06
Beef Cattle (case 2) (D=59)	3.349E+03	3.424E+03	0.000E+00
Beef Cattle (case 3) (D=59)	4.998E+03	5.176E+03	0.000E+00
Beef Cattle (case 4) (D=59)	4.241E+03	4.266E+03	0.000E+00
Dairy Cattle (case 1) (D=64)	6.696E+03	6.703E+03	0.000E+00
Dairy Cattle (case 2) (D=64)	1.475E+04	1.440E+04	1.011E-03
Dairy Cattle (case 3) (D=64)	3.213E+03	7.131E+03	0.000E+00

Constraint violation *v(x)* for the achieved best solution x is calculated using the formula, $v(x) = \frac{\sum_{i=1}^{p} G_i(x) + \sum_{j=p+1}^{m} H_j(x)}{m}$

where, $G_i(x) = \begin{cases} g_i(x), & if\ g_i(x) > 0 \\ 0, & if\ g_i(x) \le 0 \end{cases}$, $H_j(x) = \begin{cases} |h_j(x)|, & if\ |h_j(x)| - 0.0001 > 0 \\ 0, & if\ |h_j(x)| - 0.0001 \le 0 \end{cases}$

g is inequality constraints, h is equality constraints, and m is total no. of constraints.

within a limited space. Furthermore, the search space exploration plots of other EAs are not shown in order to avoid plot redundancy.

In order to check the computational complexity of ASHEA compared to other EAs, the convergence flow of the algorithms towards the optimum OF value examined. The test functions possess the diversity in characteristics and dimensionality are selected for this purpose. Two unconstrained optimization problems with different characteristics, namely the plate shaped *Booth* function and the valley shaped *Rosenbrock* function, are taken into consideration to test the convergence rate of ASHEA. Four diverse problems of varied categories and dimensions from CEC 2011 RWOPs are also presented to check the convergence rate. These plots are illustrated in figure 6 on a log-log scale to show the iterations effectively. The simplicity of the ASHEA is proved from its better comparable convergence rates towards optimum OF value as compared to other nine well known EAs and three hybridized EAs. The convergence also proves ASHEA's capabilities to perform better on diverse problems with higher dimensions.

4.2 *Nonparametric tests*

The current study also subjects the results of considered optimization problems to nonparametric tests. These are used to see if the difference between ASHEA and the selected EAs is statistically significant. For this purpose, Friedman's test and then Wilcoxon's signed-rank test post hoc analysis with a significant level of 0.05 are employed. These tests are conducted on problems considered in the current study. The results of the ELD instance 5 problem of CEC 2011 RWOPs, which has 140 dimensions, are shown in the tables.

Table 5 and Table 6 show the results of Friedman's test and Wilcoxon's test, respectively, with a critical value of 89 for 25 runs as per CEC guidelines [50]. Because the asymptotic significance value is less than the significance level, Friedman's test null hypothesis is rejected. Consequently, ASHEA differs significantly from other selected EAs. For the considered problem, the pairwise results of Wilcoxon's signed-rank test for all pairs of ASHEA with other selected EAs yield p-values less than the statistically significant level. This shows that the ASHEA is significantly different from other EAs. These pairs are significantly different for other problems also. Therefore, the results from experimental studies of ASHEA and selected EAs are valuable for deriving findings.

4.3 *Implementation of ASHEA on CEC 2020 RWSOCOPs Test Suite*

After verifying leading results compared to other EAs with dominancy, the ASHEA is implemented on the CEC 2020 RWSOCOPs full test suite to check its effectiveness. This complete test suite has 57 problems in all from six distinct disciplines. Figure 7 illustrates the ASHEA simulation results, together with the best known feasible OF values. These best known feasible OF values are taken from the competition organizing committee guidelines. To visualize the results properly, the OF values are presented with rescale. The bars for functions 3 and 32 are not visible in the graph since they have large negative values of -4.529E+03 and -3.067E+04, respectively. Nevertheless, ASHEA was still able to match these functions favorably. Figure 7 makes it obvious that, in the majority of cases, simulated results from ASHEA are in good agreement with the best-known OF values. In Table 7, the best ASHEA OF values are reported compared to the best known feasible OF values. Calculation of *v(x)* following the CEC rules is also presented to show the constraint satisfaction requirements. The brackets adjacent to the problem name denote the dimensions of the underlying problems. The results show that the ASHEA gives expected outputs in most of the problems of CEC 2020 RWSOCOPs with satisfaction of constraints.

5. Conclusion

A novel algorithm, ASHEA, for the solution of single objective unconstrained and constrained optimization problems is proposed in current research. An adaptive switching strategy of the global search and the local search effectively strives to find a better solution for a range of problems in standard test suites of CEC 2011 RWOPs and CEC 2020 RWSOCOPs. The archive pool incorporates the previous best search solutions to give optimum solutions with superior convergence compared to other well-known EAs. The specific findings and conclusions are:

- A total of 92 optimization problems are explored in the experimental evaluation of the proposed algorithm.
- Compared to the other eight well-known EAs, the ASHEA provides better results and convergence.
- In a significant number of cases, particularly for high dimensional problems of CEC 2011 RWOPs, the performance of ASHEA is superior to other well-known EAs and hybrid algorithms.
- Statistical analysis shows that the switching mechanism helps provide better solutions and convergence as compared to the other eight well-known EAs.
- Statistical test results distinguish the proposed algorithm from other well-known EAs.
- The performance of ASHEA is comparable with the top-ranking algorithms of the CEC 2020 RWSOCOPs competition.

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