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APPLICATION OF SOFT COMPUTING

Snail Homing and Mating Search algorithm: a novel bio-inspired metaheuristic algorithm

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Abstract

In this paper, a novel Snail Homing and Mating Search (SHMS) algorithm is proposed. It is inspired from the biological behaviour of the snails. Snails continuously travel to find food and a mate, leaving behind a trail of mucus that serves as a guide for their return. Snails tend to navigate by following the available trails on the ground and responding to cues from nearby shelter homes. The proposed SHMS algorithm is investigated by solving several unimodal and multimodal functions. The solutions are validated using standard statistical tests such as two-sided and pairwise signed rank Wilcoxon test and Friedman rank test. The solutions obtained from the SHMS algorithm exhibited superior robustness as well as search space exploration capabilities with less computational cost. The real-world application of the SHMS algorithm is successfully demonstrated in the engineering design domain by solving three cases of design and economic optimization Shell and Tube Heat Exchanger (STHE) problem. The objective function value and other statistical results obtained using SHMS algorithm are compared with other well-known metaheuristic algorithms. For Solving STHE Case 1 the SHMS algorithm achieved 0.5–35% minimization of the total cost. For Case 2, 0.6–29% minimization of the total cost has been attained. Furthermore, for Case 3, 0.3%, 0.4% and 52% minimization of total cost is achieved when compared with the ARGA & CI, GA, and original study, respectively. The analysis regarding the convergence of the SHMS algorithm is discussed in detail. The contributions in this paper have opened up several avenues for further applicability of the algorithm for solving complex real-world problems.

Keywords Snail Homing and Mating Search algorithm · Metaheuristic · Shell and Tube Heat Exchanger problem · Bio-inspired optimization

1 Introduction

Several nature inspired metaheuristic algorithms so far have been proposed by the researchers. These algorithms are classified into several sub-domains (Kale and Kulkarni 2021) such as (i) biology-based/evolutionary algorithms, (ii) swarm algorithms, (iii) socio inspired algorithms and (vi) physics and chemical based algorithms. Evolutionary Algorithms (EAs) mimic the evolution of the biological species. EAs are derived using the operators such as crossover and mutation. The most commonly used EA is Genetic Algorithm (GA) (Holland 1992) used these operators to generate the optimum solution. There are several other algorithms such as Differential Evolution, Evolutionary Programming (Fogel et al. 1966), Genetic Programming, Evolutionary Strategies (Michalewicz and Schoenauer 1996) are few of the notable algorithms. The

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concept of swarm optimization algorithm was adopted from the literature proposed by Happener and Grenarder (1990). Based on this, Kennedy and Eberhart (1997) pro posed Particle Swarm Optimization (PSO). It mimics the foraging behavior of flock of birds/school of fishes. The other well-known swarm algorithms are Ant Colony Optimization (ACO) (Colorni et al. 1991), Cat Swarm Optimization (CSO) (Chu et al. 2006), Cuckoo Search (CS) (Yang and Deb 2009), Firefly Algorithm (FA) (Yang 2010a), Bat Algorithm (BA) (Yang 2010a), Snake Optimizer (Hashim and Hussien 2022), Prairie Dog Optimization Algorithm (Ezugwu et al. 2022), Dwarf Mongoose Optimization Algorithm (Agushaka et al. 2022), etc. The socio inspired algorithms that draw inspiration from the social behaviors and dynamics observed in the nature and society. These algorithms are mainly classified based on social ideologies, sports, social and cultural interaction and colonization. The algorithms associated with these are as follows: Ideology Algorithm (IA) (Huan et al. 2017), Election Algorithm (EA) (Emami and Derakshan 2015) and Election Campaign Optimization (ECO) (Lv et al. 2010), League Championship Algorithm (LCA) (Kashan 2009), Teaching Learning Based Optimization (TLBO) (Rao, et al. 2011), Cohort Intelligence (CI) (Kulkarni et al. 2013), Social Learning Optimization (SLO) (Liu et al. 2016) algorithm, human-inspired metaheuristic algorithm (Dehghani et al. 2022), etc. The physics and chemical based algorithms such as Simulated Annealing (Yao 1995), Harmony Search Algorithms (Geem et al. 2001), Ray Optimization (Kaveh and Khayatazad 2012), Optical Inspired Algorithm (OIA) (Kashan 2015), Colliding Bodies Optimization (CBO) (Kaveh and Mahdavi 2014), RIME Optimization Algorithm (Su et al. 2023), and Artificial Hummingbird Algorithm (Zhao et al. 2022). Th ese algorithms have been widely applied to solved the complex problems from different domains such as design engineering, structural engineering, manufacturing problems, combinatorial optimization, power system, clustering, image processing, wireless system, heat transmission system, etc.

The recent advancement in problem-solving techniques integrates an optimistic approach with artificial neural network architecture, along with Legendre polynomial-based algorithms known as the LNN-GNDO-SQP algorithm. This hybrid algorithm combines the concepts of Legendre polynomial-based artificial neural networks (LNN) with an optimization strategy incorporating generalized normal distribution optimization (GNDO) and sequential quadratic programming (SQP) methods (Khan et al. 2021). In a subsequent development by Khan et al. (2022d), a hybrid algorithm referred to as LeNN-WOA-NM, utilizes the strengths of the LNN, Whale Optimization Algorithm (WOA) and the Nelder–Mead Algorithm (NM). This technique was specifically modeled for solving complex computational models, such as the Lorenz Chaotic Attractor (LCA) and the Double Scroll Attractor (DSA), including variations with and without filters, utilizing Chua's circuits (Khan et al. 2022c). Furthermore, Khan et al. (2022b) extended the LeNN-WOA-NM approach to analyze the dynamics of the prey-predator system with

Fig. 1 Snail path and trail following diagram ___________ indicates the path and – – – – – – – – indicates the trail

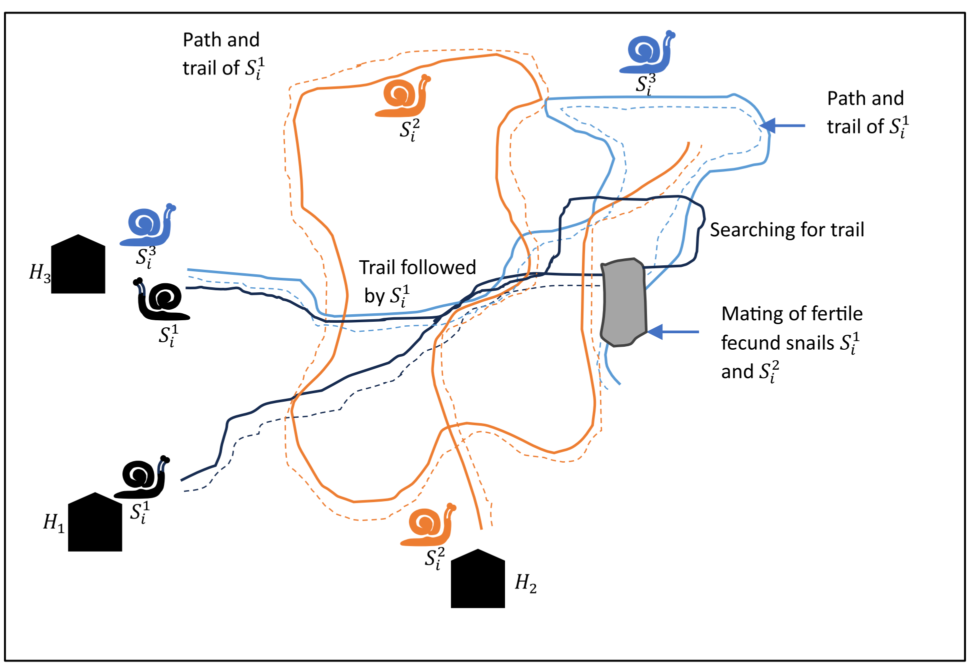


Fig. 2 Flowchart of SHMS Algorithm

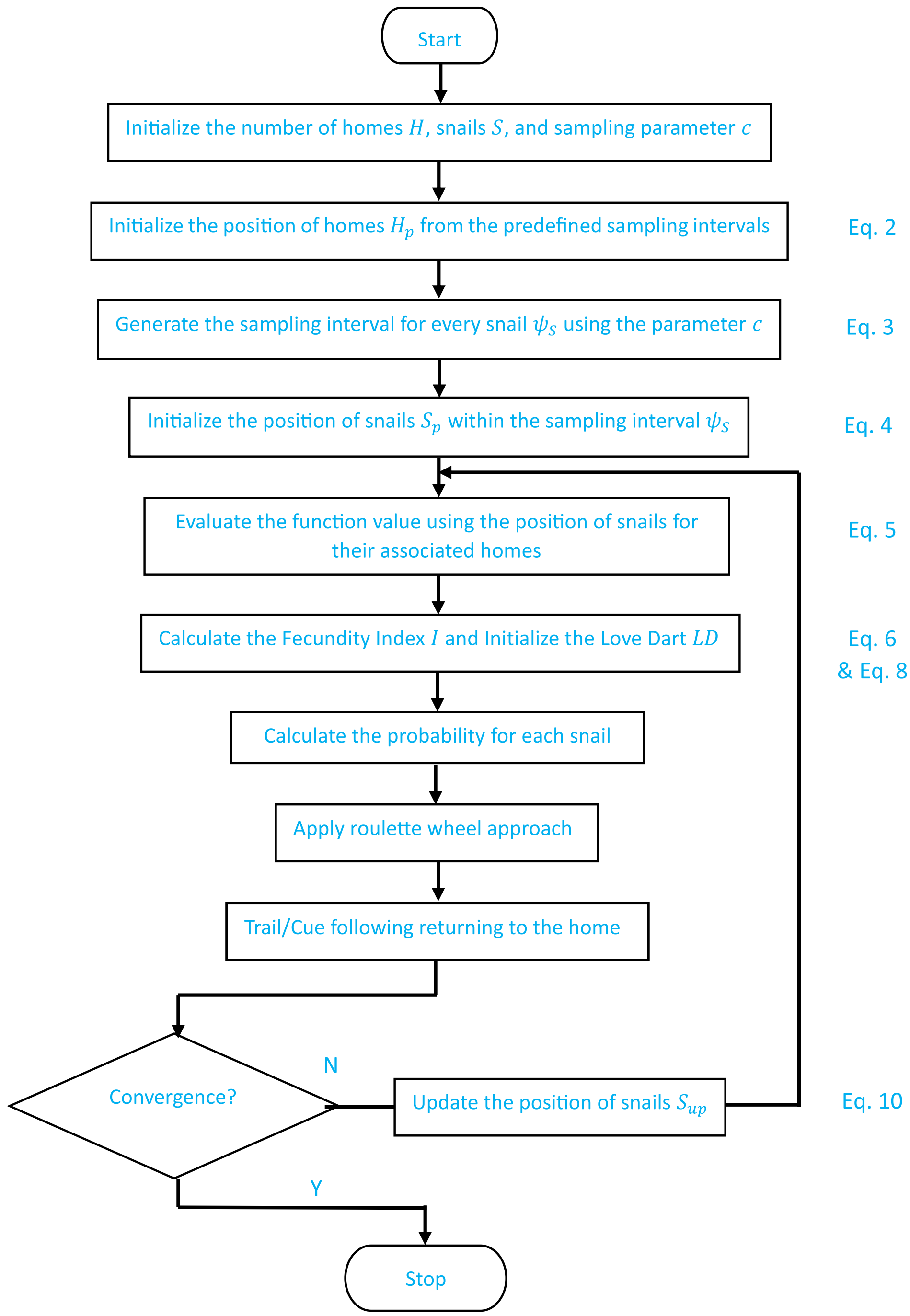


Table 1 Details of unimodal benchmark functions

No	Type	Function	Dimensions	Range	F_{min}
F1	US	Sphere	30, 100, 500, 1000	$[-100, 100]^d$	0
F2	UN	Schwefel 2.22	30, 100, 500, 1000	$[-10, 10]^d$	0
F3	UN	Schwefel 1.2	30, 100, 500, 1000	$[-100, 100]^d$	0
F4	US	Schwefel 2.21	30, 100, 500, 1000	$[-100, 100]^d$	0
F5	UN	Rosenbrock	30, 100, 500, 1000	$[-30, 30]^d$	0
F6	US	Step	30, 100, 500, 1000	$[-100, 100]^d$	0
F7	US	Quartic	30, 100, 500, 1000	$[-128, 128]^d$	0

Table 2 Details of multi-modal benchmark functions

No	Type	Function	Dimensions	Range	F_{min}
F8	MS	Schwefel	30, 100, 500, 1000	$[-500, 500]^d$	$-418.9829 \times n$
F9	MS	Rastrigin	30, 100, 500, 1000	$[-5.12, 5.12]^d$	0
F10	MN	Ackley	30, 100, 500, 1000	$[-32, 32]^d$	0
F11	MN	Griewank	30, 100, 500, 1000	$[-600, 600]^d$	0
F12	MN	Penalized	30, 100, 500, 1000	$[-50, 50]^d$	0
F13	MN	Penalized2	30, 100, 500, 1000	$[-50, 50]^d$	0

Table 3 Details of fixed-dimension multi-modal benchmark functions

No	Type	Function	Dimensions	Range	F_{min}
F14	FM	Foxholes	2	$[-65, 65]^d$	1
F15	FM	Kowalik	4	$[-5, 5]^d$	0.0003
F16	FM	Six Hump Camel	2	$[-5, 5]^d$	-1.0316
F17	FM	Branin	2	$[-5, 5]^d$	0.398
F18	FM	Goldstein-Price	2	$[-2, 2]^d$	3
F19	FM	Hartman 3	3	$[1, 3]^d$	-3.86
F20	FM	Hartman 6	6	$[0, 1]^d$	-3.32
F21	FM	Shekel 5	4	$[0, 10]^d$	-10.1532
F22	FM	Shekel 7	4	$[0, 10]^d$	-10.4028
F23	FM	Shekel 10	4	$[0, 10]^d$	-10.5363

immigrant prey. This hybrid algorithm demonstrates its efficacy in tackling diverse computational challenges. In another domain, the study investigates the steady two-phase flow of a nanofluid within a permeable duct, incorporating thermal radiation, magnetic field effects, and external forces. Khan et al. (2022b) introduces ANN-AOA-IPA technique, which combines the artificial neural network with arithmetic optimization algorithm (AOA) and interior point algorithm (IPA). A feedforward ANN-AOA-SQP combines AOA and SQP for global and local search optimization, respectively (Khan et al. 2022a). The Marine Predator Algorithm (MPA) (Khunkitti et al. 2022) and two-archive Harris Hawk Optimization (TwoArchHHO) (Khunkitti et al. 2023) are introduced for solving many-objective power flow problems.

The metaheuristic algorithms are stochastic in nature and do not guarantee optimal solutions to all classes of problems. It has been proven in No-Free-Lunch theorem (Wolpert and Macready 1997). It necessitates to explore the search to obtain the better solutions. This motivates to introduce a new nature inspired algorithm referred as Snail Homing and Mating Search (SHMS) algorithm to solve the wide variety of problems. The SHMS algorithm is inspired from the living habitat of snails. The scientific name of the snail is gastropoda. The snails are found in aquatic systems such as lakes, ponds, rivers and oceans, meaning they can live in both marine systems and freshwater. SHMS algorithm exhibits the trail following behavior (Wells and Buckley 1972; McFaruume 1980) in the search of mate and searching home.

Contributions of the proposed work are as follows:

- Introducing a novel Snail Homing and Mating Search (SHMS) algorithm inspired from the living habitat of the snails.
- Several linear and nonlinear benchmark function are solved to investigate the performance of SHMS algorithm and compared with latest metaheuristic algorithms. The SHMS achieved superior results as compared to other algorithms.

Table 4 Results of benchmark functions (F1–F13), with 30 dimensions

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
Fl	Best	5.44E-269	1.37E + 03	6.81E-29	2.27E-07	2.43E-87	1.97E-100	1.01E-01
	Worst	6.05E-198	4.27E + 03	3.14E-26	2.17E-06	2.01E-69	2.26E-95	1.00E + 04
	Mean	2.01,199	2.37E + 03	2.59E-27	7.88E-07	8.04E-71	1.66E-96	1.66E + 03
	STD	0.00E + 00	6.17E + 02	5.83E-27	5.15E-07	3.72E-70	4.36E-96	3.78E + 03
F2	Best	2.87E-136	1.13E + 01	1.29E-17	1.35E-06	5.07E-59	1.57E-50	8.00E-02
	Worst	2.58E-102	2.77E + 01	4.34E-16	8.00E-06	2.16E-48	1.11E-48	7.00E + 01
	Mean	8.72E-104	1.91E + 01	9.02E-17	3.82E-06	7.41E-50	1.89E-49	2.92E + 01
	SID	4.71E-103	3.55E + 00	8.98E-17	1.54E-06	3.94E-49	2.79E-49	2.03E + 01
F3	Best	4.92E-217	4.07E + 03	9.78E-08	2.78E + 03	1.02E + 04	2.76E-26	3.45E + 03
	Worst	2.35E-143	2.29E + 04	7.58E-04	7.39E + 03	6.08E + 04	2.93E-21	4.48E + 04
	Mean	7.83E-145	9.20E + 03	4.02E-05	5.03E + 03	4.18E + 04	3.35E-22	2.23E + 04
	STD	4.29E-144	4.24E + 03	1.46E-04	1.32E + 03	1.32E + 04	6.76E-22	1.19E + 04
F4	Best	2.57E-134	1.57E + 01	6.93E-08	1.33E + 01	5.27E + 00	1.02E-42	5.39E + 01
	Worst	2.84E-102	2.80E + 01	6.17E-06	2.11E + 01	8.61E + 01	3.41E-40	8.28E + 01
	Mean	1.03E-103	2.14E + 01	7.54E-07	1.64E + 01	4.94E + 01	9.51E-41	6.77E + 01
	STD	5.18E-103	3.51E + 00	1.16E-06	2.39E + 00	2.79E + 01	1.07E-40	8.29E + 00
F5	Best	1.96E-05	1.48E + 05	2.61E + 01	1.51E + 01	2.72E + 01	2.66E + 01	1.17E + 02
	Worst	2.56E-02	1.62E + 06	2.88E + 01	1.85E + 02	2.84E + 01	2.84E + 01	7.99E + 07
	Mean	6.50E-03	5.15E + 05	2.70E + 01	7.31E + 01	2.76E + 01	2.72E + 01	2.69E + 06
	STD	7.15E-03	3.37E + 05	7.53E-01	3.94E + 01	3.94E-01	4.23E-01	1.45E + 07
F6	Best	2.43E-07	1.19E + 03	9.91E-05	1.07E-06	1.00,01	3.37E-07	2.80,01
	Worst	6.58E-06	3.55E + 03	1.47E + 00	1.24E-01	8.78E-01	5.71E-05	1.95E + 04
	Mean	2.43E-06	2.35E + 03	7.34E-01	4.26E-03	3.80E-01	1.06E-05	2.66E + 03
	STD	1.89E-06	5.34E + 02	3.06E-01	2.25E-02	1.91E-01	1.28E-05	5.18E + 03
F7	Best	4.26E-06	1.00,01	6.31E-04	1.94E-02	1.60E-04	4.27E-04	9.10,02
	Worst	7.61E-04	8.91E-01	6.15E-03	8.19E-02	1.46E-02	2.66E-03	8.25E + 00
	Mean	2.52E-04	3.77E-01	2.35E-03	5.03E-02	3.24E-03	1.27E-03	1.33E + 00
	STD	2.05E-04	2.10E-01	1.34E-03	1.51E-02	3.45E-03	5.77E-04	2.58E + 00
F8	Best	− 1.25E + 04	− 5.10E + 03	− 7.31E + 03	− 9.37E + 03	− 1.25E + 04	− 9.54E + 03	− 1.00E + 04
	Worst	− 1.21E + 04	− 2.69E + 03	− 4.69E + 03	− 4.88E + 03	− 7.98E + 03	− 5.86E + 03	− 6.47E + 03
	Mean	− 1.25E + 04	− 3.82E + 03	− 5.99E + 03	− 6.89E + 03	− 9.69E + 03	− 7.39E + 03	− 8.51E + 03
	STD	1.00E + 02	6.19E + 02	6.14E + 02	1.14E + 03	1.50E + 03	9.60E + 02	7.76E + 02
F9	Best	0.00E + 00	1.08E + 02	5.68E-14	3.59E + 01	0.00E + 00	0.00E + 00	7.57E + 01
	Worst	0.00E + 00	2.11E + 02	1.93E + 01	1.66E + 02	0.00E + 00	4.52E + 01	2.61E + 02
	Mean	0.00E + 00	1.48E + 02	2.00E + 00	7.96E + 01	0.00E + 00	2.08E + 01	1.55E + 02
	STD	0.00E + 00	2.16E + 01	4.07E + 00	3.10E + 01	0.00E + 00	9.68E + 00	4.15E + 01
F10	Best	8.88E-16	6.71E + 00	7.19E-14	9.29E-05	8.84E-16	4.44E-15	5.58E-01
	Worst	8.88E-16	1.20E + 01	1.35E-13	8.73E-04	7.95E-15	7.99E-15	2.00E + 01
	Mean	8.88E-16	1.02E + 01	9.70E-14	3.44E-04	4.08E-15	5.98E-15	1.40E + 01
	STD	0.00E + 00	1.30E + 00	1.55E-14	1.62E-04	2.35E-15	1.79E-15	7.67E + 00
F11	Best	0.00E + 00	1.22E + 01	0.00E + 00	2.77E-06	0.00E + 00	0.00E + 00	6.32E-01
	Worst	0.00E + 00	3.24E + 01	2.93E-02	3.53E-02	1.89E-01	1.20E-04	9.10E + 01
	Mean	0.00E + 00	2.11E + 01	4.70E-03	6.41E-03	2.21E-02	4.98E-06	8.37E + 00
	STD	0.00E + 00	5.28E + 00	8.48E-03	7.85E-03	5.38E-02	2.23E-05	2.34E + 01

Table 4 (continued)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F12	Best	1.72E-08	9.28E + 00	1.26E-02	7.85E-05	5.89E-03	6.03E-10	2.08E + 00
	Worst	1.29E-06	3.58E + 03	1.15E-01	1.96E + 00	3.17E-01	1.81E-05	5.04E + 03
	Mean	3.79E-07	2.74E + 02	5.22E-02	1.32E-01	2.95E-02	1.25E-06	1.80E + 02
	STD	3.32E-07	6.87E + 02	2.56E-02	3.72E-01	5.49E-02	3.53E-06	9.18E + 02
F13	Best	8.67E-07	1.36E + 04	6.35E-02	1.01E-04	1.44E-01	4.00E-02	4.14E + 00
	Worst	8.85E-05	9.43E + 05	1.05E + 00	2.89E-01	1.37E + 00	1.01E + 00	1.91E + 03
	Mean	1.10E-05	1.66E + 05	6.10E-01	4.78E-02	5.38E-01	4.38E-01	1.24E + 02
	STD	1.56E-05	2.15E + 05	2.63E-01	7.61E-02	3.19E-01	2.69E-01	3.82E + 02

No		BBO	DE	SSA	GSA	IPO	**SHMS**
Fl	Best	3.15E + 00	7.46E-05	2.75E-08	2.11E-16	1.82E-12	**0.00E + 00**
	Worst	6.33E + 00	7.89E-04	8.75E-07	8.65E-03	3.88E-10	**0.00E + 00**
	Mean	4.47E + 00	3.36E-04	2.07E-07	2.88E-04	4.76E-11	**0.00E + 00**
	STD	7.54E-01	1.83E-04	2.17,07	1.58E-03	8.42E-11	**0.00E + 00**
F2	Best	3.90E-01	1.54E-03	2.55E-01	5.64E-08	6.77E-08	**0.00E + 00**
	Worst	6.00E-01	5.95E-03	8.00E + 00	1.19E + 00	1.27E-05	**0.00E + 00**
	Mean	5.05E-01	3.48E-03	2.39E + 00	1.40E-01	8.28E-07	**0.00E + 00**
	SID	4.53E-02	1.00E-03	1.72E + 00	3.34E-01	2.37E-06	**0.00E + 00**
F3	Best	2.51E + 02	2.17E + 04	4.40E + 02	6.57E + 02	1.30E + 00	**0.00E + 00**
	Worst	1.00E + 03	5.36E + 04	5.37E + 03	1.77E + 03	4.53E + 00	**0.00E + 00**
	Mean	4.98E + 02	3.64E + 04	1.83E + 03	1.09E + 03	2.41E + 00	**0.00E + 00**
	STD	1.49E + 02	7.01E + 03	1.02E + 03	3.11E + 02	7.86E-01	**0.00E + 00**
F4	Best	1.21E + 00	6.27E + 00	5.22E + 00	4.27E + 00	2.41E-02	**0.00E + 00**
	Worst	2.12E + 00	1.75E + 01	1.52E + 01	1.12E + 01	8.47E-02	**0.00E + 00**
	Mean	1.56E + 00	9.40E + 00	1.06E + 01	7.43E + 00	4.59E-02	**0.00E + 00**
	STD	2.00E-01	2.32E + 00	2.54E + 00	1.95E + 00	1.48E-02	**0.00E + 00**
F5	Best	4.99E + 01	2.75E + 01	2.51E + 01	2.46E + 01	1.34E + 02	**2.89E + 01**
	Worst	1.64E + 03	2.38E + 02	1.08E + 03	3.27E + 02	3.96E + 02	**2.90E + 01**
	Mean	2.24E + 02	6.00E + 01	1.85E + 02	8.34E + 01	2.27E + 02	**2.90E + 01**
	STD	3.60E + 02	6.31E + 01	2.46E + 02	6.72E + 01	7.44E + 01	**2.24E-02**
F6	Best	1.37E + 00	7.32E-05	8.02,08	1.16E-16	0.00E + 00	**0.00E + 00**
	Worst	3.17E + 00	5.72E-04	6.62E-05	5.48E-03	4.00E + 00	**0.00E + 00**
	Mean	2.36E + 00	2.65E-04	9.76E-06	1.83E-04	9.33E-01	**0.00E + 00**
	STD	4.18,01	1.47E-04	1.61E-05	1.00E-03	1.17E + 00	**0.00E + 00**
F7	Best	6.34E-03	3.00E-02	6.10,02	2.22E-02	9.85E-03	**3.27E-04**
	Worst	2.67E-02	7.44E-02	3.17E-01	1.60E-01	4.36E-02	**1.62E-02**
	Mean	1.62E-02	4.90E-02	1.71E-01	8.69E-02	2.75E-02	**4.88E-03**
	STD	5.71E-03	1.15E-02	7.63E-02	3.90E-02	9.80E-03	**3.53E-03**
F8	Best	− 9.04E + 03	− 7.59E + 03	− 9.33E + 03	− 3.34E + 03	− 4.12E + 03	**0.00E + 00**
	Worst	− 7.01E + 03	− 6.05E + 03	− 6.14E + 03	− 1.70E + 03	− 2.52E + 03	**0.00E + 00**
	Mean	− 8.10E + 03	− 6.72E + 03	− 7.32E + 03	− 2.47E + 03	− 3.28E + 03	**0.00E + 00**
	STD	5.65E + 02	3.51E + 02	7.84E + 02	3.72E + 02	3.60E + 02	**0.00E + 00**
F9	Best	2.59E + 01	1.29E + 02	2.98E + 01	1.39E + 01	9.25E + 00	**0.00E + 00**
	Worst	8.01E + 01	1.74E + 02	9.55E + 01	4.68E + 01	3.17E + 01	**0.00E + 00**
	Mean	5.22E + 01	1.57E + 02	5.05E + 01	2.92E + 01	1.68E + 01	**0.00E + 00**
	STD	1.30E + 01	1.06E + 01	1.58E + 01	7.25E + 00	4.32E + 00	**0.00E + 00**

Table 4 (continued)

No		BBO	DE	SSA	GSA	IPO	SHMS
F10	Best	3.80E-01	3.04E-03	1.34E + 00	7.68E-09	1.61E + 00	**4.44E-16**
	Worst	7.63E-01	7.78E-03	6.28E + 00	1.16E + 00	3.83E + 00	**4.44E-16**
	Mean	5.90E-01	5.19E-03	2.99E + 00	6.95E-02	2.30E + 00	**4.44E-16**
	STD	9.94E-02	1.32E-03	1.19E + 00	2.66E-01	4.82E-01	**0.00E + 00**
F11	Best	9.32E-01	3.26E-04	1.59E-03	1.21E + 01	1.02E-03	**0.00E + 00**
	Worst	1.07E + 00	1.29E-01	6.12E-02	4.75E + 01	4.30E-02	**0.00E + 00**
	Mean	1.01E + 00	1.44E-02	1.69E-02	2.88E + 01	1.10E-02	**0.00E + 00**
	STD	2.46E-02	3.48E-02	1.26E-02	6.76E + 00	9.04E-03	**0.00E + 00**
F12	Best	2.94E-03	5.02E-05	1.44E + 00	1.04E-01	3.05E-02	**0.00E + 00**
	Worst	1.38E-02	1.46E-03	1.43E + 01	4.34E + 00	1.46E + 00	**0.00E + 00**
	Mean	8.11E-03	3.92E-04	7.24E + 00	2.01E + 00	3.75E-01	**0.00E + 00**
	STD	2.47E-03	4.13E-04	3.26E + 00	1.13E + 00	3.69E-01	**0.00E + 00**
F13	Best	8.53E-02	2.20E-04	2.09E-02	4.00E-02	6.38E-02	**1.74E + 00**
	Worst	1.80E-01	7.14E-03	4.88E + 01	3.69E + 01	2.71E-01	**3.00E + 00**
	Mean	1.23E-01	1.60E-03	1.80E + 01	1.17E + 01	1.21E-01	**2.76E + 00**
	STD	2.52E-02	1.59E-03	1.41E + 01	8.46E + 00	4.09E-02	**3.11E-01**

The bold values refers to the solution obtained by proposed SHMS algorithm

– Three cases of the design and economic optimization of the STHE problem have been solved.

The organization of the paper is as follows: Sect. 2 describes the natural behavior of snails. The mathematical formulation of SHMS algorithm followed by the flowchart and graphical representation is presented in Sect. 3. Solution to unimodal (UM) and multimodal (MM) benchmark test function using SHMS algorithm and its statistical comparison along with results discussion are presented in Sect. 4. Section 5 represents the performance of SHMS algorithm by solving three cases of design and economic optimization STHE problem. The conclusions and future recommendations are presented in Sect. 6. An appendix illustrating the SHMS mechanism is provided in the appendix provided at the end of the manuscript.

2 Snail Homing and Mating Search (SHMS) algorithm

In this section, the behavior of snails is explained in terms of SHMS algorithm. The mechanism of SHMS algorithm comprises of homing, mate searching, trail following returning to the home. SHMS algorithm is a bio-inspired, population-based optimization method capable of handling complex linear and nonlinear optimization problems across various domains. It leverages principles from nature to iteratively improve a population of potential solutions, ultimately finding the best solution to the given problem.

2.1 Biological background

The snails and slugs are basically classified as hermaphroditic gastropods. The class comprises of aquatic, i.e., salt water, fresh water as well as land or terrestrial snails living in humid areas. They have been evolving by continuously adapting to the changing environment. Their basic motivations are satisfying hunger, thirst, finding hiding place or a shelter and reproduce. As hermaphroditic gastropods possess both the egg and sperm gametes which gives them the opportunity to self-fertilize. The snails are in general vegetarian, so to maintain the necessary metabolism and calcium level they keep searching for food (Alfaro 2007). To facilitate the locomotion associated with it as well as mate-searching, they must constantly produce costly mucus which necessarily requires water supply. The mucus lubrication is very necessary for their stomach foot glide across the surfaces. In order to reduce the water evaporation rate and avoid predators, snails generally take shelter in cool and humid places where moisture is available. As the snails are basically trail following gastropods, it is important to mention that the production of mucus trails is the most energy costly component of the snail locomotion (Ng et al. 2013; Hawkins and Hartnoll 1983). Snails do have eyes however they are not able to see far neither they can identify the colors (Chernorizov et al. 1994). So, they follow the mucus trail available on the ground and cues (air-borne chemical smell) arising from nearby home/nest or from the other snails (Arey and Crozier 1918, 1921). In

Table 5 Results of benchmark functions (F1–F13), with 100 dimensions

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
Fl	Best	4.37E-260	9.85E + 03	3.22E-13	1.75E + 03	7.24E-84	2.00E-92	3.00E + 04
	Worst	2.77E-193	2.44E + 04	8.28E-12	3.29E + 03	1.65E-69	1.68E-89	8.90E + 04
	Mean	1.35E-194	1.38E + 04	1.89E-12	2.43E + 03	5.62E-71	1.30E-90	5.84E + 04
	STD	0.00E + 00	3.24E + 03	1.69E-12	4.00E + 02	3.02E-70	3.09E-90	1.30E + 04
F2	Best	1.75E-139	6.96E + 01	1.31E-08	1.72E + 01	2.78E-56	2.55E-47	1.95E + 02
	Worst	4.65E-103	1.06E + 02	5.88E-08	5.20E + 01	1.02E-48	1.48E-45	3.39E + 02
	Mean	1.66E-104	8.92E + 01	3.85E-08	2.65E + 01	6.24E-50	4.27E-46	2.42E + 02
	STD	8.49E-104	9.79E + 00	1.07E-08	7.18E + 00	2.02E-49	4.36E-46	2.80E + 01
F3	Best	2.06E-208	2.98E + 04	3.91E + 01	1.54E + 05	6.46E + 05	5.39E-14	1.17E + 05
	Worst	3.71E-132	1.86E + 05	2.93E + 03	2.33E + 05	1.71E + 06	1.16E-08	3.35E + 05
	Mean	1.28E-133	9.60E + 04	6.03E + 02	2.14E + 05	1.06E + 06	7.90E-10	2.34E + 05
	STD	6.77E-133	3.64E + 04	6.81E + 02	1.56E + 04	2.92E + 05	2.51E-09	6.22E + 04
F4	Best	2.62E-129	2.41E + 01	1.49E-01	8.88E + 01	2.74E + 01	7.36E-39	8.77E + 01
	Worst	2.74E-100	4.00E + 01	2.37E + 00	9.76E + 01	9.77E + 01	4.44E-37	9.74E + 01
	Mean	9.17E-102	3.07E + 01	5.79E-01	9.53E + 01	8.22E + 01	1.17e-0.37	9.36E + 01
	STD	5.00E-101	3.75E + 00	4.84E-01	1.81E + 00	1.67E + 01	1.09E-37	2.11E + 00
F5	Best	4.67E-04	2.44E + 06	9.59E + 01	4.28E + 06	9.77E + 01	9.68E + 01	6.30E + 07
	Worst	2.88E-01	7.32E + 06	9.81E + 01	2.10E + 07	9.81E + 01	9.84E + 01	2.56E + 08
	Mean	5.12E-02	4.75E + 06	9.77E + 01	1.17E + 07	9.79E + 01	9.76E + 01	1.50E + 08
	STD	7.27E-02	1.34E + 06	5.87E-01	3.66E + 06	2.15E-01	3.78E-01	5.84E + 07
F6	Best	3.29E-06	1.04E + 04	6.88E + 00	1.36E + 03	2.10E + 00	4.72E + 00	2.79E + 04
	Worst	3.51E-03	1.89E + 04	1.32E + 01	3.29E + 03	6.92E + 00	9.46E + 00	1.00E + 05
	Mean	7.23E-04	1.44E + 04	1.00E + 01	2.41E + 03	4.26E + 00	7.39E + 00	5.91E + 04
	STD	1.00E-03	2.38E + 03	1.55E + 00	4.63E + 02	1.25E + 00	1.08E + 00	1.45E + 04
F7	Best	9.38E-06	3.15E + 00	2.54E-03	9.39E + 00	5.81E-05	5.17E-04	5.24E + 01
	Worst	4.68E-04	1.34E + 01	1.08E-02	2.06E + 01	1.27E-02	3.20E-03	5.24E + 02
	Mean	1.83E-04	7.55E + 00	6.72E-03	1.37E + 01	3.53E-03	1.77E-03	2.41E + 02
	STD	1.38E-04	2.64E + 00	2.26E-03	3.33E + 00	3.52E-03	6.45E-04	1.11E + 02
F8	Best	− 4.15E + 04	− 1.06E + 04	− 2.01 e + 04	− 1.92E + 04	− 4.18E + 04	− 2.34E + 04	− 2.58E + 04
	Worst	− 4.12e − F04	− 6.28E + 03	− 5.85E + 03	− 8.89E + 03	− 2.52E + 04	− 1.05E + 04	− 1.82E + 04
	Mean	− 4.14E + 04	− 7.62E + 03	− 1.58E + 04	− 1.36E + 04	− 3.40E + 04	− 1.69E + 04	− 2.17E + 04
	STD	5.28E + 01	1.13E + 03	3.05E + 03	3.09E + 03	5.69E + 03	2.71E + 03	1.83E + 03
F9	Best	0.00E + 00	6.66E + 02	1.38E-10	6.44E + 02	0.00E + 00	0.00E + 00	7.43E + 02
	Worst	0.00E + 00	8.35E + 02	2.39E + 01	1.08E + 03	0.00E + 00	0.00E + 00	1.00E + 03
	Mean	0.00E + 00	7.36E + 02	8.83E + 00	8.92E + 02	0.00E + 00	0.00E + 00	8.64E + 02
	STD	0.00E + 00	4.13E + 01	6.15E + 00	1.19E + 02	0.00E + 00	0.00E + 00	7.54E + 01
F10	Best	8.88E-16	1.09E + 01	7.13E-08	7.59E + 00	8.88E-16	4.44E-15	1.94E + 01
	Worst	8.88E-16	1.32E + 01	3.21E-07	9.84E + 00	7.99E-15	7.99E-15	2.03E + 01
	Mean	8.88E-16	1.19E + 01	1.30E-07	8.68E + 00	4.08E-15	7.63E-15	1.99E + 01
	STD	0.00E + 00	6.76E-01	6.01E-08	5.81E-01	1.94E-15	1.05E-15	1.31E-01
F11	Best	0.00E + 00	9.56E + 01	1.93E-13	1.48E + 01	0.00E + 00	0.00E + 00	3.55E + 02
	Worst	0.00E + 00	1.77E + 02	3.18E-02	3.22E + 01	0.00E + 00	0.00E + 00	7.09E + 02
	Mean	0.00E + 00	1.23E + 02	5.30E-03	2.29E + 01	0.00E + 00	0.00E + 00	5.33E + 02
	STD	0.00E + 00	2.15E + 01	1.09E-02	4.15E + 00	0.00E + 00	0.00E + 00	1.05E + 02
F12	Best	4.01E-07	4.25E + 02	1.46E-01	1.09E + 07	1.83E-02	7.43E-02	5.11E + 07
	Worst	6.36E-05	6.15E + 05	5.08E-01	5.79E + 07	1.30E-01	1.62E-01	6.24E + 08
	Mean	6.55E-06	1.21E + 05	3.07E-01	2.26E + 07	5.34E-02	1.17E-01	2.84E + 08
	STD	1.25E-05	1.30E + 05	7.64E-02	1.01E + 07	2.89E-02	2.31E-02	1.62E + 08

Table 5 (continued)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F13	Best	3.39E-05	7.78E + 05	5.76E + 00	1.74E + 07	1.26E + 00	6.62E + 00	1.76E + 08
	Worst	2.88E-03	8.58E + 06	7.51E + 00	8.77E + 07	4.62E + 00	9.92E + 00	1.14E + 09
	Mean	7.54E-04	3.39E + 06	6.72E + 00	5.33E + 07	2.75E + 00	8.09E + 00	5.71E + 08
	STD	7.67E-04	2.04E + 06	3.97E-01	1.87E + 07	9.29E-01	9.62E-01	2.90E + 08

No		BBO	DE	SSA	GSA	IPO	**SHMS**
Fl	Best	1.66E + 02	2.44E + 03	7.65E + 02	2.74E + 03	3.59E-01	**0.00E + 00**
	Worst	2.64E + 02	5.31E + 03	2.73E + 03	6.84E + 03	2.72E + 00	**0.00E + 00**
	Mean	2.17E + 02	3.50E + 03	1.51E + 03	4.25E + 03	1.01E + 00	**0.00E + 00**
	STD	2.26E + 01	7.32E + 02	4.62E + 02	8.52E + 02	6.69E-01	**0.00E + 00**
F2	Best	9.57E + 00	3.40E + 01	2.94E + 01	1.26E + 01	4.08E + 00	**0.00E + 00**
	Worst	1.26E + 01	8.40E + 01	1.25E + 02	3.38E + 01	1.01E + 01	**0.00E + 00**
	Mean	1.01E + 01	6.26E + 01	5.13E + 01	1.84E + 01	6.53E + 00	**0.00E + 00**
	STD	7.06E-01	1.20E + 01	1.63E + 01	4.78E + 00	1.48E + 00	**0.00E + 00**
F3	Best	3.90E + 04	3.04E + 05	1.65E + 04	8.84E + 03	2.90E + 03	**0.00E + 00**
	Worst	7.08E + 04	5.73E + 05	1.01 e + 05	2.64E + 04	9.60E + 03	**0.00E + 00**
	Mean	5.01E + 04	4.76E + 05	5.10E + 04	1.54E + 04	4.76E + 03	**0.00E + 00**
	STD	8.35E + 03	6.00E + 04	2.45E + 04	4.59E + 03	1.30E + 03	**0.00E + 00**
F4	Best	1.54E + 01	9.02E + 01	2.30E + 01	1.63E + 01	8.64E + 00	**0.00E + 00**
	Worst	2.75E + 01	9.80E + 01	3.75E + 01	2.32E + 01	1.37E + 01	**0.00E + 00**
	Mean	2.04E + 01	9.49E + 01	2.92E + 01	1.95E + 01	1.06E + 01	**0.00E + 00**
	STD	2.93E + 00	1.85E + 00	3.46E + 00	1.90E + 00	1.30E + 00	**0.00E + 00**
F5	Best	4.19E + 03	2.42E + 06	4.71E + 04	3.66E + 04	5.28E + 03	**2.89E + 01**
	Worst	7.36E + 03	8.88E + 06	2.55E + 05	2.63E + 05	2.59E + 04	**2.90E + 01**
	Mean	5.31E + 03	5.34E + 06	1.31E + 05	1.15E + 05	1.07E + 04	**2.90E + 01**
	STD	9.20E + 02	1.61E + 06	5.60E + 04	6.87E + 04	3.85E + 03	**1.64E-02**
F6	Best	1.76E + 02	2.38E + 03	6.53E + 02	2.96E + 03	3.40E + 01	**0.00E + 00**
	Worst	2.99E + 02	4.81E + 03	2.72E + 03	8.75E + 03	1.40E + 03	**0.00E + 00**
	Mean	2.30E + 02	3.39E + 03	1.52E + 03	4.65E + 03	1.27E + 02	**0.00E + 00**
	STD	2.57E + 01	6.31E + 02	4.43E + 02	1.10E + 03	2.50E + 02	**0.00E + 00**
F7	Best	8.27E-02	3.39E + 00	1.50E + 00	2.15E + 00	9.33E-01	**9.29E-05**
	Worst	1.68E-01	1.21E + 01	4.72E + 00	9.99E + 00	3.60E + 01	**2.53E-02**
	Mean	1.25E-01	6.56E + 00	2.75E + 00	4.38E + 00	4.49E + 00	**6.30E-03**
	STD	2.63E-02	2.14E + 00	7.48E-01	1.82E + 00	7.89E + 00	**5.78E-03**
F8	Best	− 2.55E + 04	− 1.37E + 04	− 2.59E + 04	− 6.02E + 03	− 1.36E + 04	**− 4.84E + 03**
	Worst	− 2.02E + 04	− 1.09E + 04	− 1.79E + 04	− 2.87E + 03	− 4.91E + 03	**− 2.24E + 01**
	Mean	− 2.25E + 04	− 1.18E + 04	− 2.14E + 04	− 4.05E + 03	− 1.07E + 04	**− 1.23E + 03**
	STD	1.03E + 03	6.65E + 02	1.73E + 03	7.99E + 02	1.93E + 03	**1.09E + 03**
F9	Best	2.55E + 02	9.10E + 02	1.54E + 02	1.37E + 02	2.40E + 02	**0.00E + 00**
	Worst	3.98E + 02	1.02E + 03	3.03E + 02	2.65E + 02	3.43E + 02	**0.00E + 00**
	Mean	3.17E + 02	9.80E + 02	2.35E + 02	1.93E + 02	2.79E + 02	**0.00E + 00**
	STD	3.33E + 01	2.85E + 01	3.87E + 01	3.64E + 01	2.58E + 01	**0.00E + 00**
F10	Best	3.18E + 00	7.87E + 00	8.38E + 00	3.54E + 00	4.27E + 00	**4.44E-16**
	Worst	3.56E + 00	1.00E + 01	1.23E + 01	6.83E + 00	6.45E + 00	**4.44E-16**
	Mean	3.42E + 00	9.11E + 00	1.01E + 01	4.96E + 00	4.93E + 00	**4.44E-16**
	STD	1.19E-01	6.18E-01	1.10E + 00	7.62E-01	5.55E-01	**0.00E + 00**

Table 5 (continued)

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F11	Best	2.65E + 00	1.64E + 01	6.66E + 00	6.10E + 02	3.47E-01	**0.00E + 00**
	Worst	3.59E + 00	5.61E + 01	2.20E + 01	7.86E + 02	1.09E + 00	**0.00E + 00**
	Mean	3.17E + 00	3.13E + 01	1.34E + 01	6.92E + 02	8.22E-01	**0.00E + 00**
	STD	2.01E-01	8.05E + 00	3.60E + 00	4.12E + 01	2.48E-01	**0.00E + 00**
F12	Best	1.22E + 00	3.46E + 06	1.20E + 01	4.70E + 00	5.24E + 00	**0.00E + 00**
	Worst	1.27E + 01	1.94E + 07	5.70E + 01	1.93E + 01	8.15E + 00	**0.00E + 00**
	Mean	4.05E + 00	9.18E + 06	3.23E + 01	1.17E + 01	6.92E + 00	**0.00E + 00**
	STD	2.41E + 00	4.31E + 06	9.77E + 00	3.91E + 00	8.03E-01	**0.00E + 00**
F13	Best	9.06E + 00	6.15E + 06	1.60E + 02	1.86E + 02	5.39E + 00	**9.99E + 00**
	Worst	1.34E + 01	3.56E + 07	5.85E + 04	3.02E + 04	1.60E + 02	**1.00E + 01**
	Mean	1.13E + 01	1.68E + 07	6.04E + 03	4.90E + 03	3.59E + 01	**1.00E + 01**
	STD	1.18E + 00	7.34E + 06	1.19E + 04	7.72E + 03	4.23E + 01	**2.91E-03**

The bold values refers to the solution obtained by proposed SHMS algorithm

addition to utilize the mucus trails left behind by every snail to search for food, water, shelter and mates, the trails are also being used for homing, self-organization, identifying conspecifics as well as discriminating between the trails laid by males and females.

2.2 Homing and self organization

It is referred to as a behavioral pattern of returning of gastropods to the specific resting positions crevices, holes, etc. after feeding excursions (Hawkins and Hartnoll 1983; Ohgushi 1954). The homes or shelters are generally of temporal persistence for solitary as well as aggregating collective homers. According to Stephenson (1936) and Cook (1979), several snail species do not necessarily follow same trail route as they left, on the other hand, some of the species even artificially displaced or their trails are washed away they still find the trail route to home. This underscores that the snails follow the trails from the conspecifics as well as prevailing wind help in detecting the air-borne chemical cues guiding towards the resting home McFaruume (1980) and Cook (1979); however, frequent changes in wind direction forces the snails to also resort to trail following.

2.3 Mate-searching

It has three major phases, viz. locating of right species, sexual selection and sexual conflict. The mucus trail following is a complementary or alternative mate-searching strategy to air-borne chemical cues (Cook 1977; Reise 2007). The snails can identify the conspecific trails especially when are sexually aroused (Townsend 1974; Nakashima 1995). The size of the fecund females is generally larger as compared to others. The chances of following such snails are quite high as the fertility chances are much higher. In addition, the trail of infected snail is generally not followed as it may be a sterile snail. According to Lodi and Keone (2016), the mating process sets up a conflict. The sperm donor snail desires to maximize the number of eggs fertilization belonging to the receiver snail. On the other side, the sperm receiver desires to have its eggs fertilized by multiple donors and does not want all the sperms from one donor to reach the eggs. The snails while mating shoot love darts into each other's body. The chemicals contained in the successfully deployed love darts exercise to increase the chances of the donor's sperms to reach the receiver's eggs with reduced chances of wastage, while the receiver's reproductive system has been evolved to counter this donor's manipulation. More specifically, the chemicals contained in the love darts increase the number of contractions between the copulatory canal and sperm digestion sack of the receiver snail, which increases the chances of the donor's sperms to reach the sperm storage sack for egg fertilization. On the other hand, the sperm entry canal referred to as diverticulum tries to increase the number of contractions to reduce the number of donor's sperms reaching the copulatory canal. This has in fact given rise to evolution of increasingly potent love-dart mucus.

3 The SHMS algorithm

The graphical representation of SHMS algorithm is presented in Fig. 1. For the sake of explanation here $H(H = H_1, H_2, H_3)$ number of homes are considered. Each home consists of equal number of snails $S(S = S_1, \ldots, S_i, \ldots, S_n)$. Every snail S_i initializes its position within the vicinity of its home. Snails continuously travel to find food and a mate, leaving behind a trail of mucus that serves as a guide for their return. They tend to navigate by following the available trails on the ground and responding to cues from nearby shelter homes. However, their ability to return to their own homes is limited, resulting in variations in the number of snails in each home. The detailed mathematical formulation of the proposed SHMS algorithm is presented in Sect. 3.

3.1 Mathematical formulation of SHMS algorithm

Consider the generalized optimization problem in minimization sense as follows:

$$\min f(\boldsymbol{X}) = f(X_1, \ldots, X_i, \ldots, X_n) i = 1,2,3,\ldots,n \tag{1}$$

$$\psi = X_i^l \leq X_i \leq X_i^u$$

Step 1: Generation of Home and Snails

Initialize the positions of H homes

$$\boldsymbol{X_H} = ((X_1), \ldots, (X_h), \ldots, (X_H)) \tag{2}$$

and the associated solutions $(f(X_1), \ldots, f(X_h), \ldots, f(X_H))$ which are referred to as homes.

Generate S snails at every home h by generating the solution in the close neighborhood of associated home solution $f(X_h)$. The close neighborhood intervals are calculated as follows.

$$\psi_S = X_h \pm c \tag{3}$$

where, c is sampling index which keeps the position of snails within the close neighborhood of its home $f(X_h)$. The sampling space of each snail is calculated only once during the test. Every snail randomly generates the position as follows:

$$\boldsymbol{X_S^h} = ((X_1), \ldots, (X_s), \ldots, (X_S))^h \tag{4}$$

The snail solutions associated with every home $h, (h = 1, \ldots, H)$ are modeled as follows:

$$\left(f\left(X_1^h\right), \ldots, f\left(X_s^h\right), \ldots, f\left(X_S^h\right)\right). \tag{5}$$

The matrix represents the arrangement of number of homes and snails.

$$\begin{array}{cccccc} \text{Homes} & X_1 & \cdots & X_h & \cdots & X_H \end{array}$$

Snails

$$\begin{bmatrix} (X_1)^1 & (X_1)^h & (X_1)^H \\ \vdots & \vdots & \vdots \\ (X_s)^1 & (X_s)^h & (X_s)^H \\ \vdots & \vdots & \vdots \\ (X_S)^1 & (X_S)^h & (X_S)^H \end{bmatrix}$$

Step 2: Calculation of Fecundity Index of snails

If the solution achieved is better as compared to the earlier fecundity of the snail increases. It is measure using fecundity index as follows:

$$I_{s^h} = \left\| \frac{\left(f\left(X_1^h\right)^{iter} - f\left(X_1^h\right)^{iter-1}\right)}{\left(f\left(X_1^h\right)^{iter} - f\left(X_1^h\right)^{iter-2}\right)} \right\|. \tag{6}$$

If $I_{s^h} \neq 0 else I_{s^h} = rand(0,1)$

The fecundity index I_{s^h} increases if the solution consistently improves and decreases if the solution degenerates. The positive value of the fecundity index I_{s^h} indicates that the snail is available for mating and negative value indicates that the snail moving towards worsen solution and hence not available for mating.

Step 3: Calculate the Probability and apply roulette wheel approach

Calculate the probability of snails

$$P_s = \frac{\left(1/f\left(X_s^h\right)\right)}{\sum_{s=1}^{S}\left(1/f\left(X_s^h\right)\right)} (s = 1, \ldots, S) \tag{7}$$

Apply the roulette wheel approach to select fecund snail for mating (Fig. 2).

Step 4: Mating and Love Dart

The snails while mating shoot love darts (LD) into each other's body. If a snail consistently exhibits increase in

Table 6 Results of benchmark functions (F1–F13), with 500 dimensions

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
Fl	Best	3.18E-249	7.46E + 04	6.20E-04	4.86E + 05	1.40E-83	3.47E-88	1.05E + 06
	Worst	2.94E-199	1.19E + 05	2.89E-03	5.62E + 05	6.09E-66	4.43E-85	1.22E + 06
	Mean	1.04E-200	9.80E + 04	1.57E-03	5.25E + 05	2.05E-67	4.13E-86	1.12E + 06
	STD	0.00E + 00	1.30E + 04	5.47E-04	2.02E + 04	1.11,66	9.06E-86	3.11E + 04
F2	Best	2.15E-131	4.49E + 02	8.12E-03	1.77E + 52	2.13E-55	4.25E-45	5.79E + 75
	Worst	1.00E-99	6.36E + 02	1.42E-02	7.09E + 117	9.69E-47	3.44E-43	1.77E + 120
	Mean	3.38E-101	5.33E + 02	1.09E-02	2.36E + 116	3.89E-48	3.95E-44	6.04E + 118
	STD	1.84E-100	4.81E + 01	1.58E-03	1.29E + 117	1.78E-47	6.78E-44	3.24E + 119
F3	Best	7.15E-196	1.00E + 06	2.33E + 05	4.74E + 06	1.49E + 07	6.47E-08	3.31E + 06
	Worst	8.95E-102	5.44E + 06	5.27E + 05	6.41E + 06	5.22E + 07	8.04E-03	6.39E + 06
	Mean	2.98E-103	2.29E + 06	3.57E + 05	5.57E + 06	3.04E + 07	6.76E-04	4.80E + 06
	STD	1.63E-102	8.31E + 05	7.70E + 04	4.80E + 05	1.00E + 07	1.99E-03	9.16E + 05
F4	Best	1.87E-136	3.44E + 01	5.69E + 01	9.83E + 01	1.62E + 01	8.57E-37	9.82E + 01
	Worst	3.49E-100	4.77E + 01	7.77E + 01	9.92E + 01	9.87E + 01	4.51E-35	9.91E + 01
	Mean	1.47E-101	3.82E + 01	6.47E + 01	9.89E + 01	8.19E + 01	8.65e-0.36	9.85E + 01
	STD	6.43E-101	2.73E + 00	5.77E + 00	3.01E-01	2.10E + 01	9.83E-36	3.71E-01
F5	Best	3.34E-03	2.16E + 07	4.93E + 02	1.72E + 09	4.91E + 02	4.94E + 02	4.64E + 09
	Worst	1.86E + 01	6.50E + 07	4.96E + 02	2.95E + 09	4.97E + 02	4.97E + 02	5.45E + 09
	Mean	3.66E + 00	4.31E + 07	4.94E + 02	2.30E + 09	4.93E + 02	4.95E + 02	5.02E + 09
	STD	4.12E + 00	1.13E + 07	3.30E-01	3.17E + 08	3.52E-01	1.13E-01	2.21E + 08
F6	Best	2.76E-04	7.35E + 04	8.75E + 01	4.72E + 05	1.89E + 01	9.06E + 01	1.05E + 06
	Worst	4.78E-01	1.20E + 05	9.44E + 01	5.73E + 05	4.73E + 01	9.82E + 01	1.21E + 06
	Mean	5.90E-02	9.65E + 04	9.14E + 01	5.29E + 05	3.24E + 01	9.42E + 01	1.15E + 06
	STD	1.03E-01	1.42E + 04	1.68E + 00	2.55E + 04	8.30E + 00	2.05E + 00	3.50E + 04
F7	Best	2.71E-06	1.74E + 02	2.62E-02	1.23E + 04	1.43E-04	5.14E-04	3.28E + 04
	Worst	5.53E-04	6.70E + 02	7.89E-02	1.91E + 04	1.40E-02	3.30E-03	4.23E + 04
	Mean	2.09E-04	3.50E + 02	5.20E-02	1.59E + 04	4.65E-03	1.67E-03	3.87E + 04
	STD	1.54E-04	1.35E + 02	1.36E-02	1.49E + 03	4.70E-03	6.18E-04	2.31E + 03
F8	Best	− 2.13e-F05	− 2.25E + 04	− 6.50E + 04	− 3.92E + 04	− 2.09E + 05	− 6.07E + 04	− 7.14E + 04
	Worst	− 2.10e-F05	− 1.34E + 04	− 4.96E + 04	− 1.84E + 04	− 1.26E + 05	− 2.57E + 04	− 5.01E + 04
	Mean	− 2.12E + 05	− 1.78E + 04	− 5.80E + 04	− 2.73E + 04	− 1.69E + 05	− 3.96E + 04	− 6.22E + 04
	STD	6.16E + 02	2.57E + 03	3.75E + 03	5.92E + 03	3.09E + 04	9.39E + 03	4.89E + 03
F9	Best	0.00e-F00	4.28E + 03	2.37E + 01	6.50E + 03	0.00E + 00	0.00E + 00	6.61E + 03
	Worst	0.00e-F00	4.86E + 03	1.61E + 02	7.02E + 03	0.00E + 00	0.00E + 00	7.27E + 03
	Mean	0.00E + 00	4.61E + 03	7.88E + 01	6.84E + 03	0.00E + 00	0.00E + 00	6.93E + 03
	STD	0.00e-F00	1.58E + 02	2.83E + 01	1.16E + 02	0.00E + 00	0.00E + 00	1.65E + 02
F10	Best	8.88E-16	1.21E + 01	1.23E-03	1.95E + 01	8.88E-16	4.44E-15	2.03E + 01
	Worst	8.88E-16	1.44E + 01	3.38E-03	1.98E + 01	7.99E-15	7.99E-15	2.05E + 01
	Mean	8.88E-16	1.30E + 01	1.90E-03	1.97E + 01	4.44E-15	7.87E-15	2.04E + 01
	STD	0.00e-F00	6.47E-01	4.40E-04	9.58E-02	2.46E-15	6.48E-16	1.49E-01
F11	Best	0.00E + 00	6.73E + 02	1.07E-04	4.18E + 03	0.00E + 00	0.00E + 00	9.83E + 03
	Worst	0.00e-F00	1.28E + 03	1.29E-01	5.16E + 03	0.00E + 00	0.00E + 00	1.06E + 04
	Mean	0.00e-F00	9.41E + 02	3.35E-02	4.71E + 03	0.00E + 00	0.00E + 00	1.02E + 04
	STD	0.00E + 00	1.74E + 02	4.90E-02	2.14E + 02	0.00E + 00	0.00E + 00	2.86E + 02
F12	Best	8.97E-09	8.55E + 05	6.59E-01	4.04E + 09	2.45E-02	5.89E-01	1.05E + 10
	Worst	4.98E-04	1.47E + 07	8.21E-01	9.90E + 09	1.87E-01	7.19E-01	1.24E + 10
	Mean	4.19E-05	4.05E + 06	7.43E-01	7.44E + 09	8.59E-02	6.52E-01	1.20E + 10
	STD	9.45E-05	3.49E + 06	4.36E-02	1.53E + 09	4.24E-02	3.33E-02	5.00E + 08

Table 6 (continued)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F13	Best	3.38E-04	1.41E + 07	4.88E + 01	7.74E + 09	9.45E + 00	4.98E + 01	1.94E + 10
	Worst	1.99E-01	1.27E + 08	5.40E + 01	1.42E + 10	2.58E + 01	4.99E + 01	2.42E + 10
	Mean	2.52E-02	5.34E + 07	5.11E + 01	1.13E + 10	1.80E + 01	4.99E + 01	2.21E + 10
	STD	4.30E-02	2.83E + 07	1.25E + 00	1.63E + 09	4.12E + 00	7.42E-03	9.85E + 08

No		BBO	DE	SSA	GSA	IPO	**SHMS**
Fl	Best	6.32E + 03	4.89E + 05	7.64E + 04	5.02E + 04	9.28E + 03	**0.00E + 00**
	Worst	8.16E + 03	6.17E + 05	1.05E + 05	6.22E + 04	1.39E + 04	**0.00E + 00**
	Mean	7.15E + 03	5.63E + 05	9.33E + 04	5.57E + 04	1.13E + 04	**0.00E + 00**
	STD	5.43E + 02	2.92E + 04	8.25E + 03	2.82E + 03	1.17E + 03	**0.00E + 00**
F2	Best	2.05E + 02	1.44E + 03	4.97E + 02	2.80E + 02	1.64E + 02	**0.00E + 00**
	Worst	2.75E + 02	1.54E + 03	5.75E + 02	3.23E + 270	1.98E + 02	**0.00E + 00**
	Mean	2.29E + 02	1.50E + 03	5.31E + 02	1.08E + 269	1.81E + 02	**0.00E + 00**
	STD	1.72E + 01	3.50E + 01	2.00E + 01	1.00E + 300	9.43E + 00	**0.00E + 00**
F3	Best	1.19E + 06	8.87E + 06	5.20E + 05	3.92E + 05	1.10E + 05	**0.00E + 00**
	Worst	2.34E + 06	1.32E + 07	2.39E + 06	3.88E + 06	2.20E + 05	**0.00E + 00**
	Mean	1.55E + 06	1.16E + 07	1.24E + 06	1.17E + 06	1.48E + 05	**0.00E + 00**
	STD	2.25E + 05	1.10E + 06	6.10E + 05	6.80E + 05	2.78E + 04	**0.00E + 00**
F4	Best	4.86E + 01	9.88E + 01	3.50E + 01	2.55E + 01	1.84E + 01	**0.00E + 00**
	Worst	5.75E + 01	9.92E + 01	4.86E + 01	3.27E + 01	2.19E + 01	**0.00E + 00**
	Mean	5.27E + 01	9.89E + 01	4.03E + 01	2.87E + 01	2.04E + 01	**0.00E + 00**
	STD	2.07E + 00	1.98E-01	3.30E + 00	1.56E + 00	9.22E-01	**0.00E + 00**
F5	Best	6.08E + 05	1.75E + 09	2.75E + 07	6.49E + 06	2.31E + 06	**2.89E + 01**
	Worst	1.01E + 06	6.00E + 09	4.72E + 07	1.40E + 07	3.53E + 06	**2.90E + 01**
	Mean	8.44E + 05	2.82E + 09	3.71E + 07	8.69E + 06	2.85E + 06	**2.90E + 01**
	STD	9.37E + 04	8.04E + 08	4.14E + 06	1.62E + 06	3.81E + 05	**1.83E-02**
F6	Best	6.66E + 03	4.87E + 05	7.57E + 04	5.00E + 04	1.36E + 04	**0.00E + 00**
	Worst	8.51E + 03	6.23E + 05	1.08E + 05	6.27E + 04	2.71E + 04	**0.00E + 00**
	Mean	7.35E + 03	5.50E + 05	9.42E + 04	5.70E + 04	1.96E + 04	**0.00E + 00**
	STD	4.77E + 02	3.53E + 04	6.51E + 03	2.75E + 03	4.06E + 03	**0.00E + 00**
F7	Best	3.67E + 02	1.16E + 04	2.08E + 02	7.08E + 02	1.77E + 03	**2.60E-03**
	Worst	7.03E + 02	2.04E + 04	3.54E + 02	1.44E + 03	4.79E + 03	**2.84E-02**
	Mean	4.96E + 02	1.55E + 04	2.75E + 02	9.88E + 02	2.86E + 03	**1.02E-02**
	STD	9.00E + 01	2.19E + 03	3.96E + 01	1.74E + 02	7.30E + 02	**6.91E-03**
F8	Best	− 7.49E + 04	− 2.76E + 04	− 6.80E + 04	− 1.61E + 04	− 4.85E + 04	**− 7.90E + 03**
	Worst	− 6.62E + 04	− 2.38E + 04	− 4.93E + 04	− 6.32E + 03	− 9.29E + 03	**− 5.07E + 01**
	Mean	− 7.07E + 04	− 2.55E + 04	− 6.08E + 04	− 1.10E + 04	− 3.06E + 04	**− 2.75E + 03**
	STD	2.53E + 03	1.12E + 03	4.37E + 03	2.27E + 03	1.44E + 04	**2.76E + 03**
F9	Best	5.75E + 03	6.51E + 03	2.95E + 03	2.53E + 03	3.17E + 03	**0.00E + 00**
	Worst	6.41E + 03	7.10E + 03	3.34E + 03	2.98E + 03	3.45E + 03	**0.00E + 00**
	Mean	6.05E + 03	6.75E + 03	3.16E + 03	2.73E + 03	3.33E + 03	**0.00E + 00**
	STD	1.80E + 02	1.24E + 02	1.04E + 02	1.16E + 02	7.02E + 01	**0.00E + 00**
F10	Best	2.02E + 01	1.91E + 01	1.38E + 01	1.01E + 01	1.35E + 01	**4.44E-16**
	Worst	2.05E + 01	2.01E + 01	1.46E + 01	1.11E + 01	1.46E + 01	**4.44E-16**
	Mean	2.03E + 01	1.95E + 01	1.42E + 01	1.05E + 01	1.41E + 01	**4.44E-16**
	STD	8.64E-02	1.45E-01	2.27E-01	2.32E-01	2.56E-01	**0.00E + 00**

Table 6 (continued)

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F11	Best	2.27E + 03	4.02E + 03	7.64E + 02	8.17E + 03	8.63E + 01	**0.00E + 00**
	Worst	3.30E + 03	5.53E + 03	9.47E + 02	8.99E + 03	1.11E + 02	**0.00E + 00**
	Mean	3.02E + 03	5.03E + 03	8.46E + 02	8.618 + 03	9.618 + 01	**0.00E + 00**
	STD	2.62E + 02	3.34E + 02	5.56E + 01	2.05E + 02	5.73E + 00	**0.00E + 00**
F12	Best	3.84E + 08	4.69E + 09	2.27E + 05	1.99E + 02	1.39E + 01	**0.00E + 00**
	Worst	7.24E + 08	1.83E + 10	3.69E + 06	8.02E + 04	2.42E + 01	**0.00E + 00**
	Mean	4.95E + 08	1.13E + 10	1.39E + 06	1.46E + 04	1.92E + 01	**0.00E + 00**
	STD	8.51E + 07	4.24E + 09	7.92E + 05	1.91E + 04	2.40E + 00	**0.00E + 00**
F13	Best	8.71E + 08	7.35E + 09	1.85E + 07	1.69E + 06	6.78E + 03	**5.00E + 01**
	Worst	1.75E + 09	3.43E + 10	5.92E + 07	7.18E + 06	5.47E + 04	**5.00E + 01**
	Mean	1.35E + 09	1.47E + 10	3.32E + 07	3.89E + 06	2.73E + 04	**5.00E + 01**
	STD	2.47E + 08	6.31E + 09	8.49E + 06	1.33E + 08	1.13E + 04	**2.41E-03**

The bold values refers to the solution obtained by proposed SHMS algorithm

fecundity index, then s snails in certain vicinity using a roulette wheel approach meet with the fecund snail. The *LD* of the better solution snail are more effective. The *LD* effect is calculated as follows:

$$LD_s = \frac{1}{I_{s^h} \times \left(f\left(X_s^h\right) - f\left(X_{s_{fecund}}^h\right)\right)} \tag{8}$$

The better snail solution carries more weightage as compared with other snails.

The value of the LD_s calculated using Eq. (8) are too large hence it is normalized for computational purpose as follows:

$$LD_s = \frac{\left(LD_s - (LD_s)_{min}\right)}{(LD_s)_{max} - (LD_s)_{min}} \tag{9}$$

Further the *LD* effect is utilized to calculate the new sampling interval of the snails.

Step 5: Trail/Cue following and position update

The snail having better solution carries more weightage as compared with other snails. Generally, snails follow the trail/cues while returning to their home. There is a possibility that while returning to their home the snail may follow trail/ cues generated by other fecund snails s^h_{fecund}. It may happen that the snail s^h can get the home of other snails. According to that, the snail generates a new position in the vicinity of the current home and continue to travel. The new position is identified as follows:

$$s^h_{up} = LD_s \times \left(s^h - s^h_{fecund}\right) \tag{10}$$

In this paper, several linear and nonlinear test problems and threes cases of STHE problem are considered for the validation of proposed SHMS algorithm. The SHMS algorithm is coded in MATLAB R2022a and the simulations are run on Windows platform using 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHz processor speed and 8 BG RAM. Every individual problem is solved 30 time. The solutions obtained from SHMS algorithm are compared with other well-known nature inspire optimization algorithms discussed in following sections.

In nutshell, the objective function values are the potential local solutions and are modeled as homes. The snails are generated in the local neighborhood of these homes. The snails then start randomly searching the space. The snails leave message such as their availability for mating. Based on the proximity and better solution snails, the mating is done. It is modeled as adapting the solutions in their close neighborhood. The love darts bias the adaptation by giving weightage to the better solutions. The selected best solutions are then referred to as homes and the process continues.

4 Solution to benchmark test functions

The SHMS algorithm is validated by solving a set of benchmark functions from Abdollahzadeh et al. (2021). This set of benchmark functions consists of 2 different groups of unimodal (UM) and multi-modal (MM) functions. The function names and features of the UM and MM benchmark function are shown in Tables 1, 2, 3. Every

Table 7 Results of benchmark functions (F1–F13), with 1000 dimensions

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F1	Best	7.50E-278	1.47E + 05	1.41E-01	1.33E + 06	9.06E-84	2.06E-87	2.62E + 06
	Worst	3.06E-193	3.04E + 05	4.79E-01	1.49E + 06	5.41E-67	2.33E-84	2.83E + 06
	Mean	1.05E-194	2.16E + 05	2.42E-01	1.43E + 06	1.80E-68	2.44E-85	2.73E + 06
	STD	0.00E + 00	4.33E + 04	7.43E-02	4.49E + 04	9.88E-68	4.40E-85	4.83E + 04
F2	Best	4.21E-173	1.00E + 300	2.87E-01	1.00E + 300	2.13E-56	1.00E + 300	1.00E + 300
	Worst	2.02E-112	1.00E + 300	2.10E + 00	1.00E + 300	2.83E-47	1.00E + 300	1.00E + 300
	Mean	6.75E-114	1.00E + 300	7.17E-01	1.00E + 300	1.93E-48	1.00E + 300	1.00E + 300
	STD	3.69E-113	1.00E + 300	3.96E-01	1.00E + 300	5.68E-48	1.00E + 300	1.00E + 300
F3	Best	2.27E-219	3.96E + 06	1.15E + 06	1.83E + 07	6.83E + 07	4.55E-06	1.31E + 07
	Worst	5.26E-111	1.36E + 07	2.65E + 06	2.49E + 07	2.26E + 08	1.59E-01	2.66E + 07
	Mean	1.76E-112	8.18E + 06	1.67E + 06	2.15E + 07	1.32E + 08	1.13E-02	1.85E + 07
	STD	9.60E-112	2.44E + 06	3.22E + 05	1.82E + 06	4.84E + 07	3.16E-02	3.66E + 06
F4	Best	3.10E-143	3.61E + 01	7.28E + 01	9.91E + 01	9.05E + 00	2.61E-36	9.90E + 01
	Worst	1.34E-100	5.58E + 01	8.84E + 01	9.95E + 01	9.96E + 01	1.50E-34	9.94E + 01
	Mean	4.47E-102	4.23E + 01	7.90E + 01	9.92E + 01	8.23E + 01	2.97E-35	9.92E + 01
	STD	2.44E-101	3.75E + 00	3.21E + 00	9.52E-02	2.01E + 01	2.95E-35	1.42E-01
F5	Best	1.44E-03	5.25E + 07	1.00E + 03	6.94E + 09	9.92E + 02	9.93E + 02	1.19E + 10
	Worst	5.25E + 01	2.02E + 08	1.12E + 03	9.62E + 09	9.95E + 02	9.95E + 02	1.31E + 10
	Mean	5.80E + 00	9.78E + 07	1.02E + 03	8.51E + 09	9.93E + 02	9.94E + 02	1.24E + 10
	STD	1.11E + 01	3.42E + 07	2.12E + 01	6.35E + 08	7.07E-01	1.31E-01	2.91E + 08
F6	Best	2.26E-03	1.41E + 05	1.95E + 02	1.28E + 06	2.80E + 01	2.03E + 02	2.57E + 06
	Worst	1.05E + 00	2.91E + 05	2.06E + 02	1.47E + 06	1.17E + 02	2.18E + 02	2.75E + 06
	Mean	1.27E-01	1.99E + 05	2.00E + 02	1.41E + 06	7.29E + 01	2.13E + 02	2.72E + 06
	STD	2.06E-01	3.44E + 04	2.79E + 00	5.50E + 04	1.91E + 01	2.20E + 00	4.95E + 04
F7	Best	1.41E-05	8.87E + 02	9.98E-02	8.40E + 04	1.30E-04	8.77E-04	1.90E + 05
	Worst	9.11E-04	2.64E + 03	2.10E-01	1.28E + 05	1.87E-02	3.67E-03	2.09E + 05
	Mean	2.85E-04	1.57E + 03	1.48E-01	1.10E + 05	3.54E-03	2.01E-03	1.97E + 05
	STD	2.43E-04	4.93E + 02	3.08E-02	1.27E + 04	4.43E-03	6.18E-04	4.50E + 03
F8	Best	− 4.18E + 05	− 3.43E + 04	− 1.02E + 05	− 6.79E + 04	− 4.18E + 05	− 9.18E + 04	− 1.79E + 05
	Worst	− 3.95E + 05	− 1.98E + 04	− 1.77E + 04	− 2.46E + 04	− 2.21E + 05	− 2.75E + 04	− 7.40E + 04
	Mean	− 4.17E + 05	− 2.58E + 04	− 8.58E + 04	− 3.72E + 04	− 3.27E + 05	− 5.87E + 04	− 8.72E + 04
	STD	4.69E + 03	3.72E + 03	1.88E + 04	1.07E + 04	6.28E + 04	1.38E + 04	6.85E + 03
F9	Best	0.00E + 00	9.21E + 03	1.11E + 02	1.38E + 04	0.00E + 00	0.00E + 00	1.50E + 04
	Worst	0.00E + 00	1.00E + 04	2.90E + 02	1.46E + 04	0.00E + 00	0.00E + 00	1.58E + 04
	Mean	0.00E + 00	9.66E + 03	1.90E + 02	1.43E + 04	0.00E + 00	0.00E + 00	1.52E + 04
	STD	0.00E + 00	1.87E + 02	4.19E + 01	1.64E + 02	0.00E + 00	0.00E + 00	1.92E + 02
F10	Best	8.88E-16	1.24E + 01	1.38E-02	1.95E + 01	8.88E-16	7.99E-15	2.00E + 01
	Worst	8.88E-16	1.55E + 01	2.24E-02	2.03E + 01	4.44E-15	1.30E + 01	2.06E + 01
	Mean	8.88E-16	1.37E + 01	1.83E-02	2.00E + 01	3.01E-15	4.29E-01	2.05E + 01
	STD	0.00E + 00	8.96E-01	2.17E-03	9.92E-02	1.77E-15	2.34E + 00	1.91E-01
F11	Best	0.00E + 00	1.42E + 03	8.47E-03	1.12E + 04	0.00E + 00	0.00E + 00	2.40E + 04
	Worst	0.00E + 00	2.50E + 03	2.50E-01	1.38E + 04	0.00E + 00	1.11E-16	2.51E + 04
	Mean	0.00E + 00	1.87E + 03	5.11E-02	1.28E + 04	0.00E + 00	3.33E-17	2.46E + 04
	STD	0.00E + 00	2.73E + 02	7.61E-02	5.92E + 02	0.00E + 00	5.17E-17	3.53E + 02
F12	Best	2.19E-07	1.28E + 06	9.04E-01	2.38E + 10	3.60E-02	8.20E-01	2.79E + 10
	Worst	5.89E-04	3.48E + 07	1.88E + 00	3.85E + 10	3.03E-01	8.94E-01	3.22E + 10
	Mean	6.76E-05	1.09E + 07	1.18E + 00	3.17E + 10	1.05E-01	8.54E-01	3.04E + 10
	STD	1.44E-04	8.13E + 06	2.76E-01	4.68E + 09	6.06E-02	1.52E-02	1.01E + 09

Table 7 (continued)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F13	Best	1.93E-03	3.71E + 07	1.06E + 02	3.44E + 10	1.91E + 01	9.98E + 01	5.15E + 10
	Worst	2.89E-01	3.20E + 08	1.24E + 02	4.87E + 10	6.70E + 01	9.95E + 01	5.80E + 10
	Mean	5.76E-02	1.15E + 08	1.18E + 02	4.44E + 10	3.65E + 01	9.94E + 01	5.55E + 10
	STD	8.02E-02	6.11E + 07	5.35E + 00	3.17E + 09	1.14E + 01	1.17E-02	1.44E + 09

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F1	Best	6.00E + 05	1.49E + 06	2.12E + 05	1.22E + 05	4.10E + 04	**0.00E + 00**
	Worst	7.30E + 05	1.81E + 06	2.67E + 05	1.48E + 05	5.07E + 04	**0.00E + 00**
	Mean	6.69E + 05	1.60E + 06	2.37E + 05	1.31E + 05	4.60E + 04	**0.00E + 00**
	STD	2.99E + 04	8.51E + 04	1.30E + 04	5.62E + 03	2.32E + 03	**0.00E + 00**
F2	Best	1.00E + 300	1.00E + 300	1.11E + 03	1.17E + 263	4.39E + 02	**0.00E + 00**
	Worst	1.00E + 300	1.00E + 300	1.25E + 03	6.38E + 289	4.88E + 02	**0.00E + 00**
	Mean	1.00E + 300	1.00E + 300	1.19E + 03	3.46E + 288	4.60E + 02	**0.00E + 00**
	STD	1.00E + 300	1.00E + 300	3.14E + 01	1.00E + 300	1.04E + 01	**0.00E + 00**
F3	Best	6.81E + 06	3.62E + 07	2.37E + 06	2.99E + 06	3.28E + 05	**0.00E + 00**
	Worst	1.23E + 07	5.94E + 07	9.55E + 06	1.37E + 07	7.63E + 05	**0.00E + 00**
	Mean	9.66E + 06	4.77E + 07	5.92E + 06	6.53E + 06	5.55E + 05	**0.00E + 00**
	STD	1.60E + 06	5.67E + 06	1.92E + 06	2.56E + 06	9.61E + 04	**0.00E + 00**
F4	Best	8.27E + 01	9.88E + 01	4.00E + 01	3.13E + 01	2.24E + 01	**0.00E + 00**
	Worst	8.99E + 01	9.95E + 01	5.26E + 01	3.72E + 01	2.47E + 01	**0.00E + 00**
	Mean	8.60E + 01	9.91E + 01	4.48E + 01	3.40E + 01	2.35E + 01	**0.00E + 00**
	STD	2.03E + 00	1.40E-01	2.82E + 00	1.28E + 00	7.51E-01	**0.00E + 00**
F5	Best	7.96E + 08	1.42E + 10	9.60E + 07	2.09E + 07	1.14E + 07	**2.89E + 01**
	Worst	1.17E + 09	1.53E + 10	1.53E + 08	2.85E + 07	1.61E + 07	**2.90E + 01**
	Mean	9.58E + 08	1.48E + 10	1.14E + 08	2.47E + 07	1.36E + 07	**2.90E + 01**
	STD	8.91E + 07	2.77E + 08	1.21E + 07	1.95E + 06	1.09E + 06	**2.18E-02**
F6	Best	6.07E + 05	1.38E + 06	2.15E + 05	1.21E + 05	4.69E + 04	**0.00E + 00**
	Worst	7.21E + 05	2.27E + 06	2.54E + 05	1.48E + 05	9.84E + 04	**0.00E + 00**
	Mean	6.66E + 05	1.63E + 06	2.37E + 05	1.31E + 05	6.24E + 04	**0.00E + 00**
	STD	3.34E + 04	1.61E + 05	1.12E + 04	5.65E + 03	1.06E + 04	**0.00E + 00**
F7	Best	1.19E + 04	9.92E + 04	1.31E + 03	5.43E + 03	1.83E + 04	**2.60E-03**
	Worst	1.56E + 04	2.49E + 05	2.15E + 03	8.26E + 03	2.69E + 04	**2.84E-02**
	Mean	1.34E + 04	2.05E + 05	1.69E + 03	6.43E + 03	2.20E + 04	**1.02E-02**
	STD	1.15E + 03	5.24E + 04	1.74E + 02	7.09E + 02	2.00E + 03	**6.91E-03**
F8	Best	− 8.37E + 04	− 4.25E + 04	− 1.01E + 05	− 2.38E + 04	− 7.88E + 04	**0.00E + 00**
	Worst	− 7.22E + 04	− 3.39E + 04	− 7.11E + 04	− 9.51E + 03	− 1.60E + 04	**0.00E + 00**
	Mean	− 7.80E + 04	− 3.64E + 04	− 8.72E + 04	− 1.34E + 04	− 5.47E + 04	**0.00E + 00**
	STD	2.85E + 03	2.00E + 03	8.08E + 03	2.78E + 03	1.89E + 04	**0.00E + 00**
F9	Best	1.13E + 04	1.38E + 04	7.17E + 03	6.23E + 03	7.62E + 03	**0.00E + 00**
	Worst	1.18E + 04	1.43E + 04	7.93E + 03	7.02E + 03	8.10E + 03	**0.00E + 00**
	Mean	1.17E + 04	1.41E + 04	7.57E + 03	6.69E + 03	7.79E + 03	**0.00E + 00**
	STD	2.42E + 02	2.41E + 02	2.07E + 02	2.16E + 02	1.13E + 02	**0.00E + 00**
F10	Best	1.96E + 01	2.01E + 01	1.42E + 01	1.10E + 01	1.41E + 01	**4.44E-16**
	Worst	2.03E + 01	2.06E + 01	1.49E + 01	1.15E + 01	1.48E + 01	**4.44E-16**
	Mean	2.00E + 01	2.03E + 01	1.46E + 01	1.12E + 01	1.45E + 01	**4.44E-16**
	STD	8.64E-02	1.10E-01	1.82E-01	1.43E-01	1.51E-01	**0.00E + 00**

Table 7 (continued)

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F11	Best	5.15E + 03	1.24E + 04	1.97E + 03	1.98E + 04	4.78E + 02	**0.00E + 00**
	Worst	6.47E + 03	1.70E + 04	2.30E + 03	2.13E + 04	5.97E + 02	**0.00E + 00**
	Mean	5.86E + 03	1.45E + 04	2.07E + 03	2.05E + 04	5.44E + 02	**0.00E + 00**
	STD	3.55E + 02	1.02E + 03	8.45E + 01	3.34E + 02	2.69E + 01	**0.00E + 00**
F12	Best	7.51E + 08	3.39E + 10	5.05E + 06	5.39E + 04	2.68E + 01	**0.00E + 00**
	Worst	1.07E + 09	3.79E + 10	1.79E + 07	5.00E + 05	1.90E + 02	**0.00E + 00**
	Mean	8.87E + 08	3.68E + 10	1.11E + 07	1.88E + 05	5.47E + 01	**0.00E + 00**
	STD	8.29E + 07	1.09E + 09	3.00E + 06	1.19E + 05	3.99E + 01	**0.00E + 00**
F13	Best	2.35E + 09	6.49E + 10	1.08E + 08	9.50E + 06	3.58E + 05	**1.00E + 02**
	Worst	3.42E + 09	6.92E + 10	2.15E + 08	2.66E + 07	1.04E + 06	**1.00E + 02**
	Mean	2.78E + 09	6.70E + 10	1.46E + 08	1.60E + 07	6.38E + 05	**1.00E + 02**
	STD	2.71E + 08	1.22E + 09	2.20E + 07	4.03E + 06	1.92E + 05	**3.33E-03**

The bold values refers to the solution obtained by proposed SHMS algorithm

problem in these benchmark test cases is solved 30 times using SHMS algorithm. The following computational parameters are selected for SHMS algorithm based on preliminary trials: number of homes H = 3, number of snails S = 5 per home, and the search space interval parameter c = 0.98.

4.1 Statistical analysis

The SHMS algorithm proposed here is compared with several recent algorithms such as African Vultures Optimization Algorithm (AVOA) (Abdollahzadeh et al 2021), PSO (Simon 2008), Grey Wolf Optimizer (GWO) (Mirjalili et al. 2014), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis 2016), Farmland Fertility Algorithm (FFA) (Shayanfar and Gharehchopogh 2018), TLBO (Rao et al. 2011), Mo th-flame optimization algorithm (MFO) (Mirjalili 2015), Biogeography-Based Optimization (BBO) (Simon 2008), Differential Evolution (DE) (Simon 2008), Salp Swarm Algorithm (SSA) (Mirjalili et al. 2017), Gravitational Search Algorithm (GSA) (Rashedi et al. 2009) and Inclined Planes system Optimization (IPO) (Mozaffari et al. 2016). Note that the results for the above-mentioned algorithms were obtained from Abdollahzadeh et al 2021. The comparison of mean solution, best solution and standard deviation (Std. Dev.), mean run time (in seconds) over the 30 runs of the SHMS algorithm solving F1-F13 problems for 30, 100, 500 and 1000 dimensions are represented in Tables 4, 5, 6, 7, respectively. The purpose of performing evaluation over different dimensions is to check the Snail algorithms scalability. From the Tables 4, 5, 6, 7 it is evident that SHMS algorithm demonstrates ability to deliver high quality solutions in various dimensions. In addition, it shows the ability to solve problems having larger dimensions with same set of parameters and without affecting its performance. Table 8 shows the performance comparison of SHMS algorithm for fixed dimension MM problems F14-F23. The algorithm yields comparable results for some of these functions. However, algorithm is not efficient in solving some benchmark functions due to trapping in the local minima. The snails' behavior is visually represented through convergence plots, contour plots, and 3D mesh plots, revealing the outcomes. Figure 3a–e represents the performance of SHMS algorithm on UM benchmark test functions. For the MM benchmark test functions, the performance of SHMS algorithm presented in Fig. 4a–i. In these plots the best function values (best snails) are plotted. However, it is also important to showcase the behaviour of all the snails and their homes. The representation of homes and associated snails for two UM and MM are presented in Fig. 5. In these plots, the *triangle* refers to the homes and *dots* refer to the associated snails. From the figures it is evident that SHMS algorithm has an ability of quick convergence which obtained the solution with lesser number of iterations. The convergence plot shows the convergence of the solution, contour plot and 3D mesh plot show the search path of the snails within the function.

A pairwise comparison of SHMS algorithm with every other algorithm is carried out, i.e., the values of 30 independent runs solving every problem using SHMS algorithm are compared with every other algorithm solving 30 independent runs of these problems. For the Wilcoxon signed-rank test, the significance value α was chosen to be 0.05 with null hypothesis H0 is: There is no difference between the median of the solutions obtained by algorithm A and the median of the solutions obtained by algorithm B for the same set of test problems, i.e. median (A) = median (B). Also, to determine whether algorithm A yielded a statistically better solution than algorithm B or whether

Table 8 Results of benchmark functions (F14–F23)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO
F14	Best	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01
	Worst	2.98E + 00	1.60E + 01	1.27E + 01	7.83B + 00	1.08E + 01	9.98E-01	1.27E + 01
	Mean	1.26E + 00	5.95E + 00	4.06E + 00	1.91E + 00	2.57E + 00	9.98E-01	2.87E + 00
	STD	5.79E-01	3.76E + 00	4.18E + 00	2.07E + 00	2.54E + 00	4.12E-17	2.55E + 00
F15	Best	3.08E-04	4.20E-04	3.07E-04	3.34B-04	3.08E-04	3.07E-04	7.12E-04
	Worst	7.57E-04	5.67E-02	2.04E-02	8.75E-04	2.13E-03	2.04E-02	2.01E-02
	Mean	4.65E-04	1.07E-02	4.39E-03	5.90E-04	6.55E-04	1.09E-03	1.93E-03
	STD	1.48E-04	1.80E-02	8.13E-03	1.19B-04	4.22E-04	3.65E-03	3.75E-03
F16	Best	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00
	Worst	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00
	Mean	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00
	STD	6.78E-16	6.59E-06	1.56E-08	6.78E-16	2.02E-09	6.78E-16	6.78E-16
F17	Best	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01
	Worst	3.98E-01	8.86E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01
	Mean	3.98E-01	4.62E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01
	STD	1.69E-16	1.15E-01	1.47E-06	3.95E-12	6.06E-06	1.69E-16	1.69E-16
F18	Best	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00
	Worst	3.00E + 00	8.40E + 01	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00
	Mean	3.00E + 00	1.06E + 01	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00
	STD	0.00E + 00	1.72E + 01	3.93E-05	0.00E + 00	2.29E-04	0.00E + 00	0.00E + 00
F19	Best	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00
	Worst	− 3.86E + 00	− 3.32E + 00	− 3.85E + 00	− 3.86E + 00	− 3.79E + 00	− 3.86E + 00	− 3.86E + 00
	Mean	− 3.86E + 00	− 3.80E + 00	− 3.86E + 00	− 3.86E + 00	− 3.85E + 00	− 3.86E + 00	− 3.86E + 00
	STD	9.16E-10	1.05E-01	2.45E-03	3.48E-08	1.60E-02	2.63E-15	1.44E-03
F20	Best	− 3.32E + 00	− 3.29E + 00	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00
	Worst	− 3.20E + 00	− 1.30E + 00	− 3.09E + 00	− 3.20E + 00	− 3.07E + 00	− 3.20E + 00	− 3.14E + 00
	Mean	− 3.31E + 00	− 2.77E + 00	− 3.27E + 00	− 3.30E + 00	− 3.19E + 00	− 3.29E + 00	− 3.22E + 00
	STD	3.02E-02	4.31E-01	7.55E-02	4.43E-02	9.04E-02	5.34E-02	5.20E-02
F21	Best	− 1.02E + 01	− 1.01E + 01	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01
	Worst	− 1.02E + 05	− 6.87E − 01	− 2.68E + 00	− 4.81E + 00	− 2.63E + 00	− 2.68E + 00	− 2.63E + 00
	Mean	− 1.02E + 01	− 3.78E + 00	− 8.15E + 00	− 9.02E + 00	− 7.66E + 00	− 9.26E + 00	− 5.56E + 00
	STD	1.08E-10	2.86E + 00	2.95E + 00	1.96E + 00	2.90E + 00	2.02E + 00	3.41E + 00
F22	Best	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01
	Worst	− 1.04E + 01	− 1.60E + 00	− 1.04E + 01	− 3.68E + 00	− 2.76E + 00	− 3.61E + 00	− 2.75E + 00
	Mean	− 1.04E + 01	− 5.04E + 00	− 1.04E + 01	− 9.68E + 00	− 7.79E + 00	− 8.70E + 00	− 9.05E + 00
	STD	9.14E-11	2.92E + 00	1.32E-03	2.05E + 00	3.09E + 00	2.67E + 00	2.78E + 00
F23	Best	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01
	Worst	− 1.05E + 01	− 1.63E + 00	− 2.42E + 00	− 2.87E + 00	− 7.89E-01	− 3.84E + 00	− 2.43E + 00
	Mean	− 1.05E + 01	− 4.89E + 00	− 1.03E + 01	− 9.81E + 00	− 6.81E + 00	− 9.87E + 00	− 8.68E + 00
	STD	4.34E-11	3.20E + 00	1.48E + 00	2.14E + 00	3.34E + 00	2.04E + 00	3.16E + 00

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F14	Best	9.98E-01	9.98E-01	9.98E-01	9.98E-01	9.98E-01	**1.27E + 01**
	Worst	7.87E + 00	5.93E + 00	4.95E + 00	1.25E + 01	6.90E + 00	**1.27E + 01**
	Mean	3.27E + 00	1.39E + 00	1.39E + 00	5.41E + 00	2.61E + 00	**1.27E + 01**
	STD	2.12E + 00	1.26E + 00	8.85E-01	3.35E + 00	1.82E + 00	**0.00E + 00**

Table 8 (continued)

No		BBO	DE	SSA	GSA	IPO	**SHMS**
F15	Best	3.93E-04	3.08E-04	3.08E-04	1.17E-03	3.07E-04	**4.67E-04**
	Worst	2.04E-02	2.01E-02	6.33E-02	1.29E-02	7.14E-04	**7.65E-03**
	Mean	4.79E-03	1.14E-03	4.28E-03	4.35E-03	4.30E-04	**2.75E-03**
	STD	7.92E-03	3.64E-03	1.22E-02	2.74E-03	1.36E-04	**1.89E-03**
F16	Best	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	**− 1.03E + 00**
	Worst	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	**− 1.01E + 00**
	Mean	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	− 1.03E + 00	**− 1.03E + 00**
	STD	4.43E-12	6.78E-16	4.09E-14	4.88E-16	5.61E-16	**4.95E-03**
F17	Best	3.98E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	**3.16E + 00**
	Worst	8.92E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	**1.77E + 01**
	Mean	4.77E-01	3.98E-01	3.98E-01	3.98E-01	3.98E-01	**9.72E + 00**
	STD	1.39E-01	1.69E-16	2.29E-05	1.69E-16	2.87E-13	**3.31E + 00**
F18	Best	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	**3.22E + 00**
	Worst	8.43E + 01	3.00E + 00	3.00E + 00	3.00E + 00	3.00E + 00	**3.21E + 01**
	Mean	7.510 + 00	3.000 + 00	3.00E + 00	3.00E + 00	3.00E + 00	**8.90E + 00**
	STD	1.60E + 01	0.000 + 00	2.74E-12	4.20E-15	2.78E-15	**7.24E + 00**
F19	Best	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	**− 3.84E + 00**
	Worst	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	**− 3.13E + 00**
	Mean	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	− 3.86E + 00	**− 3.59E + 00**
	STD	3.42E-15	2.71E-15	5.26E-10	2.31E-15	2.25E-15	**2.05E-01**
F20	Best	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00	− 3.32E + 00	**− 2.55E + 00**
	Worst	− 3.20E + 00	− 3.20E + 00	− 3.15E + 00	− 3.32E + 00	− 3.20E + 00	**− 1.08E + 00**
	Mean	− 3.28E + 00	− 3.29E + 00	− 3.23E + 00	− 3.32E + 00	− 3.31E + 00	**− 1.82E + 00**
	STD	5.83E-02	5.11E-02	6.33E-02	1.61E-15	3.03E-02	**3.92E-01**
F21	Best	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01	− 1.02E + 01	**− 1.69E + 00**
	Worst	− 2.63E + 00	− 2.68E + 00	− 2.63E + 00	− 2.63E + 00	− 2.63E + 00	**− 9.28E − 01**
	Mean	− 5.07E + 00	− 9.40E + 00	− 6.30E + 00	− 7.03E + 00	− 8.07E + 00	**− 1.25E + 00**
	STD	3.24E + 00	1.99E + 00	3.53E + 00	3.68E + 00	3.29E + 00	**2.42E-01**
F22	Best	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	− 1.04E + 01	**− 3.49E + 00**
	Worst	− 2.75E + 00	− 2.75E + 00	− 2.75E + 00	− 2.77E + 00	− 2.75E + 00	**− 9.40E-01**
	Mean	− 5.96E + 00	− 9.85E + 00	− 8.89E + 00	− 9.79E + 00	− 9.89E + 00	**− 1.34E + 00**
	STD	3.47E + 00	1.85E + 00	2.850 + 00	1.90E + 00	1.94E + 00	**5.06E-01**
F23	Best	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	− 1.05E + 01	**− 1.94E + 00**
	Worst	− 1.86E + 00	− 2.87E + 00	− 2.43E + 00	− 2.43E + 00	− 2.42E + 00	**− 9.80E-01**
	Mean	− 5.28E + 00	− 1.03E + 01	− 8.53E + 00	− 9.49E + 00	− 7.81E + 00	**− 1.35E + 00**
	STD	3.55E + 00	1.40E + 00	3.42E + 00	2.72E + 00	3.49E + 00	**2.43E-01**

The bold values refers to the solution obtained by proposed SHMS algorithm

alternative hypothesis was valid, the sizes of the ranks provided by the Wilcoxon signed-rank test (T + and T −) were thoroughly examined. From Table 8 it is evident that the SHMS algorithm could not yield better results for most of the fixed dimension functions, which results in a low average value of the global solutions obtained using the SHMS algorithm. Therefore, the SHMS algorithm is not winning against any other algorithm. The algorithms with statistically better solutions for F1-F13 problems found using Wilcoxon signed-rank test for 30, 100, 500 and 1000 dimensions are presented in Tables 9, 10, 11, 12, respectively. The results highlighted that the SHMS algorithm performed significantly better than every other algorithm for the dimensions 30 and 100 as shown in Tables 9 and 10. However, it is evident from the Tables 11 and 12 that SHMS algorithm outperformed every other algorithm except AVOA due to the increase in the number of variables increases i.e., 500 and 1000. Table 13 shows the pairwise comparison of F14-F23 problems where SHMS algorithm could not yield better solutions as compared to

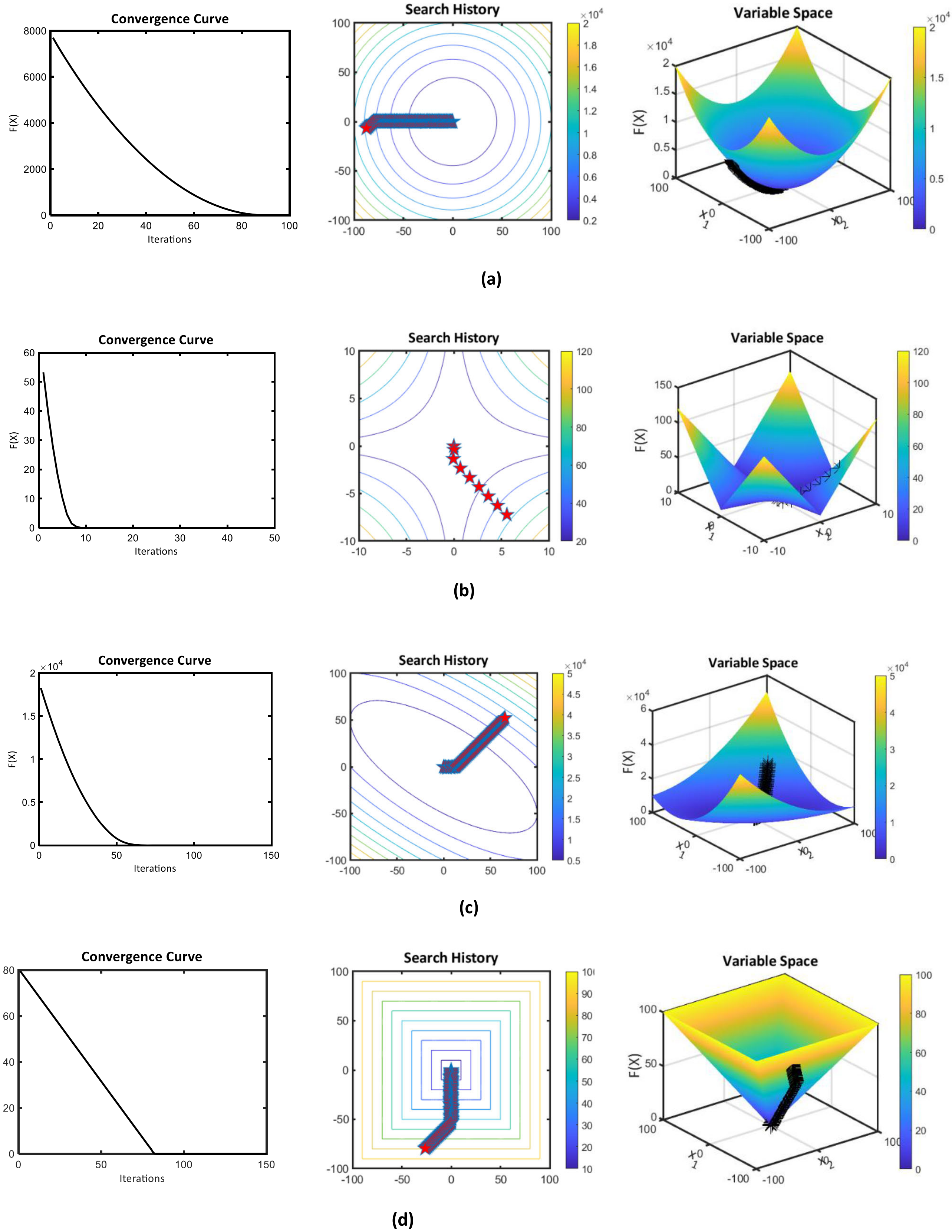


Fig. 3 The convergence curve, contour plot and 3D mesh plot of SHMS results solving unimodal benchmark test problems.**a** Sphere function, **b** Schwefel 2.22 function, **c** Schwefel 1.2 function, **d** Schwefel 2.21 function, **e** Rosenbrock function, **f** Step function, **g** Quartic function

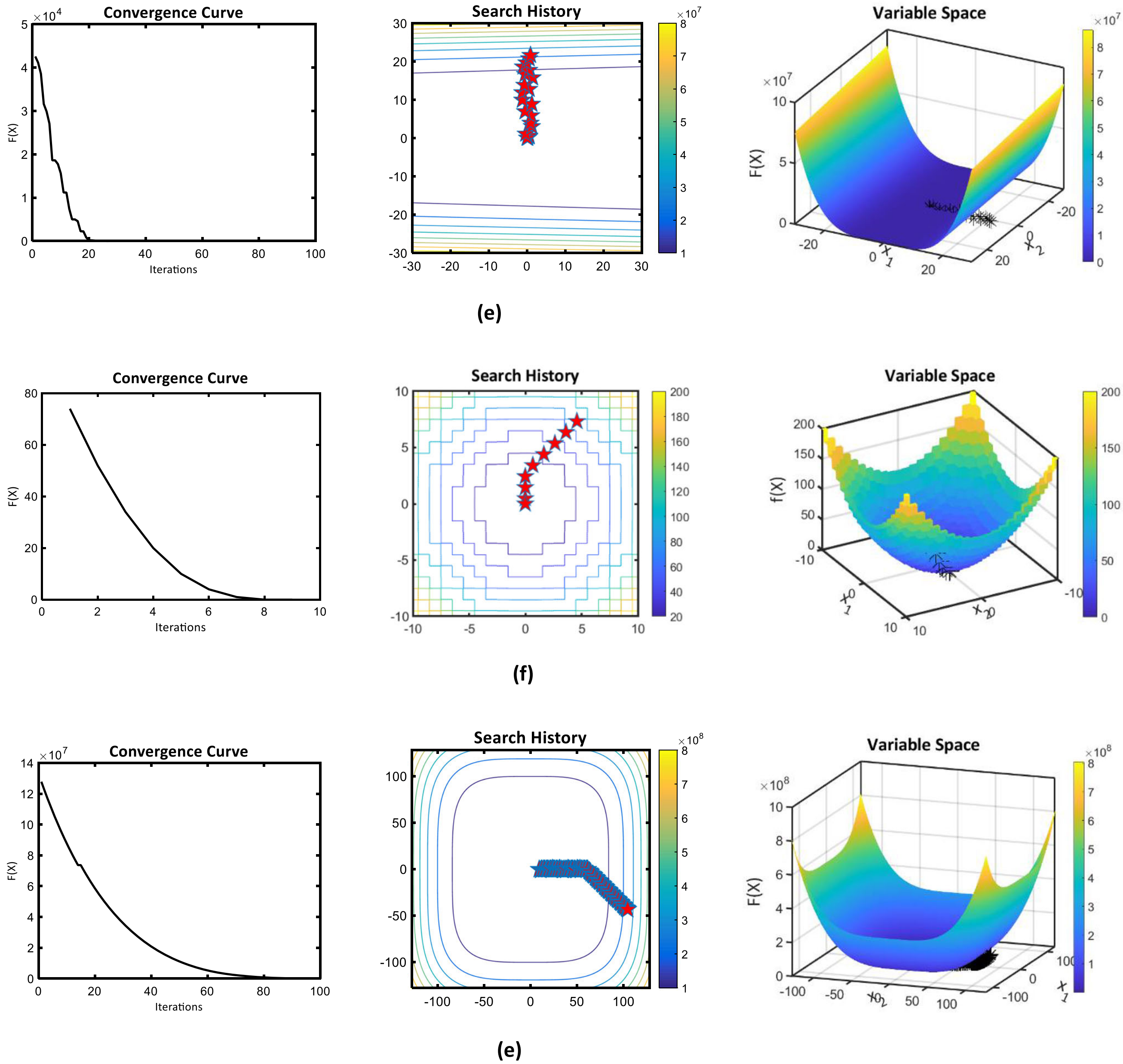


Fig. 3 continued

other algorithms. Results shown in Table 14 demonstrate that the SHMS algorithm is a robust approach with reasonable computational cost and could quickly reach in the close neighbourhood of the global optimum solution. SHMS algorithm not only has found better solutions than other optimization algorithms in the F1–F13 test functions, but it also performs faster than other optimization algorithms in terms of execution time. It even takes less running time to solve large-scale issues and confirms that the computational complexity of SHMS is less than other algorithms. In addition, for statistical analysis Friedman test is performed. The Friedman test is a nonparametric statistical method used to detect multiple test attempts. Using the one-way repeated analysis of variances the ranks were calculated for multiple algorithms by columns. Friedman test is a non-parametric test used for testing samples from populations. This test uses ranks instead of the actual values of the dependent sample difference. Since, the mean values for the AVOA algorithm were better in comparison to the SHMS algorithm, the AVOA was ranked number 1 and the SHMS as number 2. In the Friedman test, the average of optimum solutions obtained

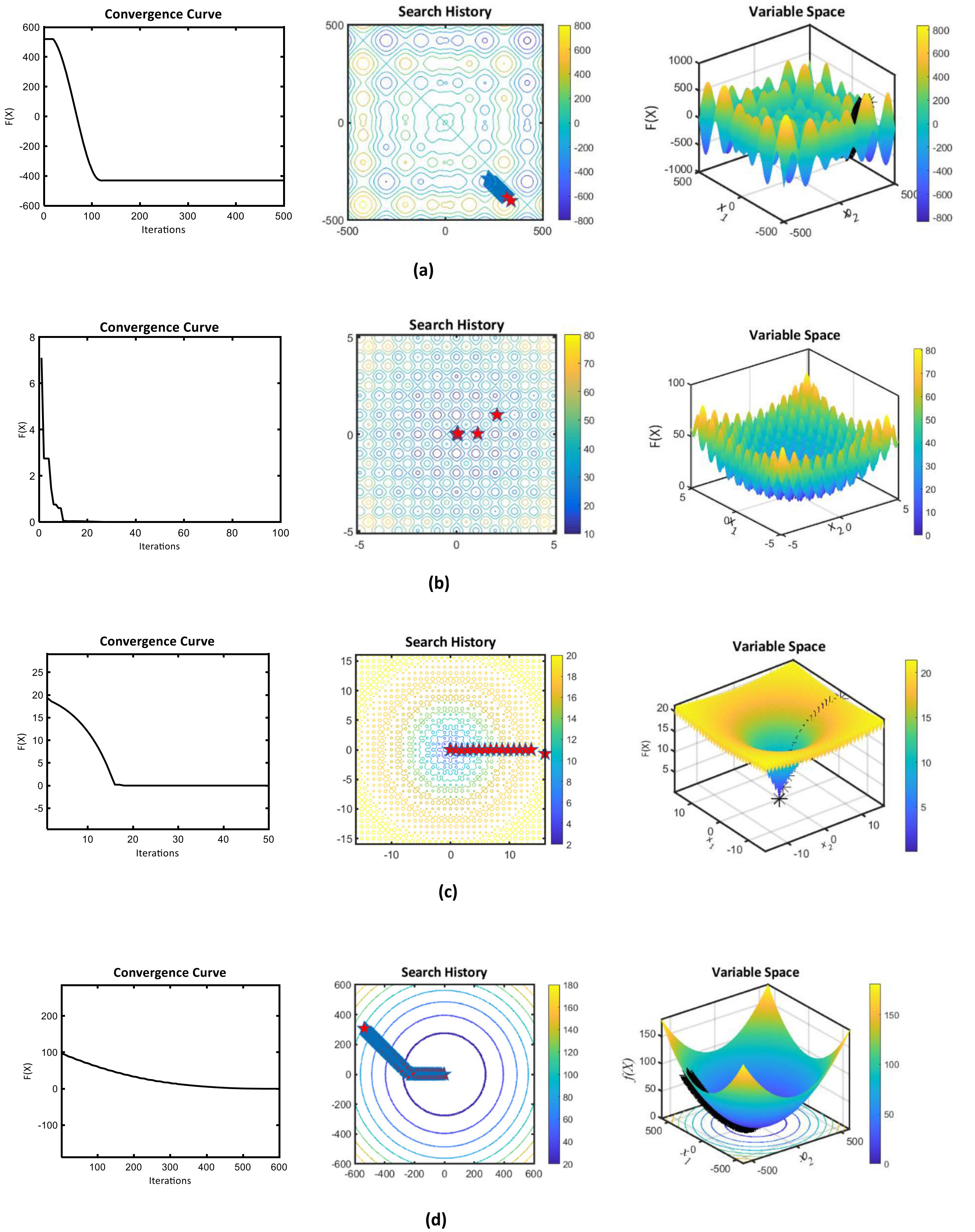
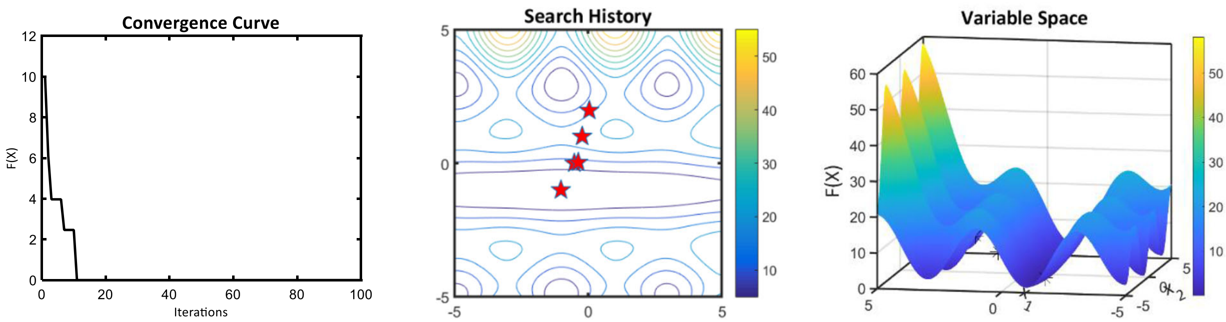
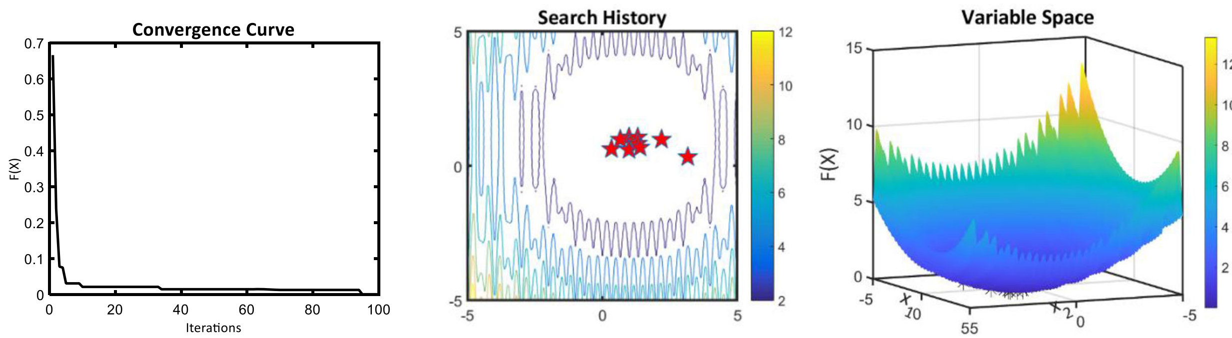


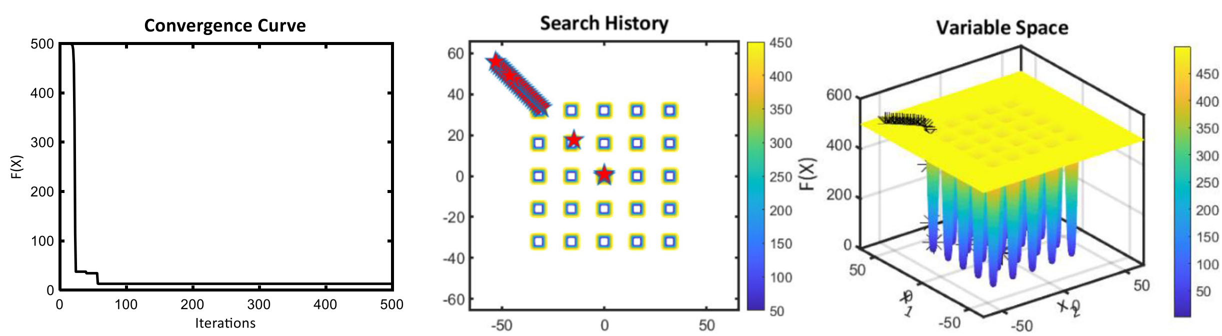
Fig. 4 The convergence curve, contour plot and 3D mesh plot of SHMS results solving multimodal benchmark test problems. **a** Schwefel function, **b** Rastrigin function, **c** Ackley function, **d** Griewank function, **e** Penalized function, **f** Penalized 2 function, **g** Foxholes function, **h** Six Hump Camel function, **i** Branin function, **j** Goldstein Price function



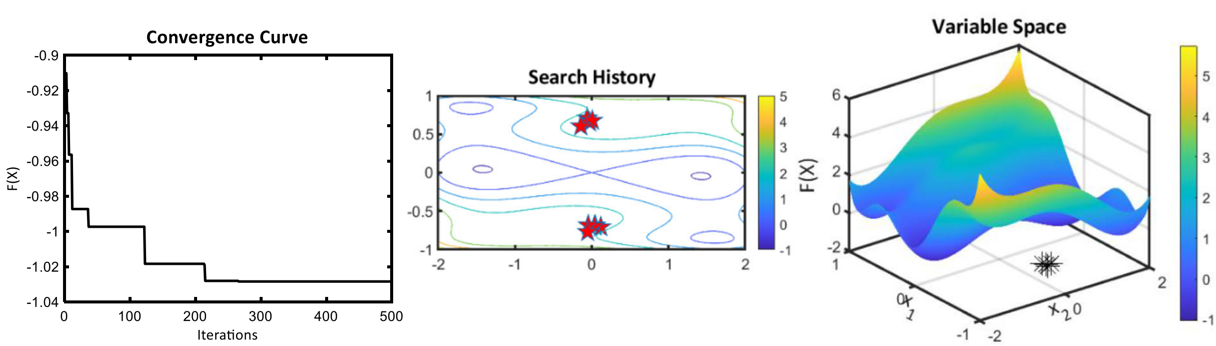
(e)



(f)

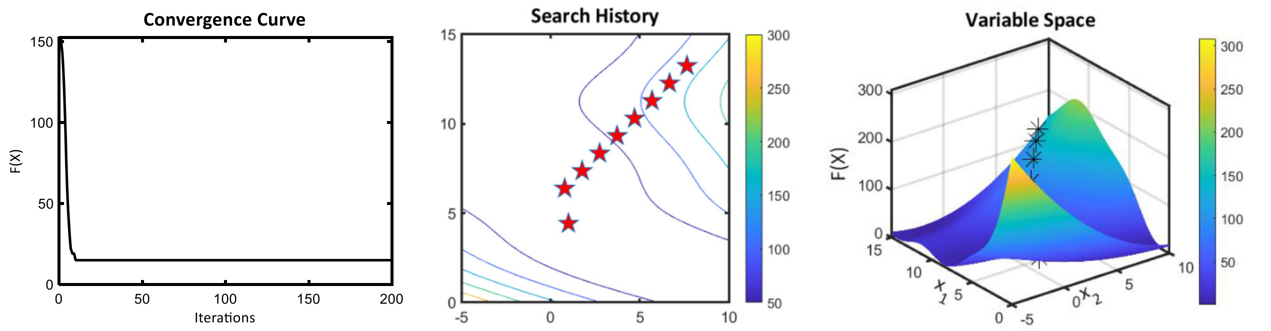


(g)

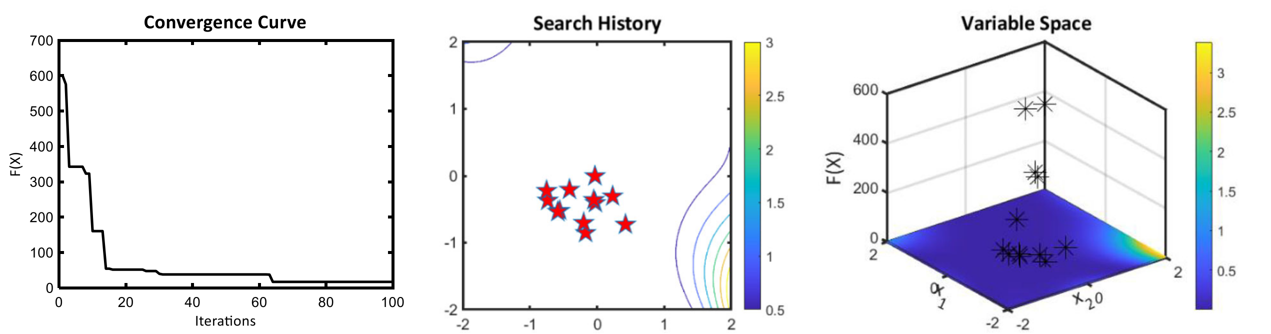


(h)

Fig. 4 continued



(i)



(i)

Fig. 4 continued

from 30 runs solving the F1–F13 problem for 30, 100, 500 and 1000 dimensions and F14–F23 problems using SHMS algorithm is compared with other algorithms solving the same benchmark test functions. The Friedman test ranks are based on the mean values obtained by the algorithms (refer to Tables 15, 16, 17, 18, 19).

5 Solution to the STHE design and economic optimization problem

The STHE problem is most widely used to test an applicability of the metaheuristic algorithms. This problem has three cases as follows:

Case 1: 4.34 (MW) heat duty, methanol-brackish water heat exchanger.
Case 2: 1.44 (MW) heat duty, kerosene-crude oil heat exchanger.
Case 3: 0.46 (MW) heat duty, distilled water-raw water heat exchanger.

The problem has been previously solved using several metaheuristic algorithms such as GA (Caputo et al. 2008), PSO (Patel and Rao 2010), ABC (Sahin et al. 2011), BBO (Hadidi and Nazari 2013), Intelligent Tuned Harmony Search Algorithm (ITHS), Improved Intelligent Tuned Harmony Search Algorithm (I-ITHS) (Turgut et al. 2014), CI (Dhavle et al. 2018), FFA (Mohanty 2016), Adaptive Range Genetic Algorithm (ARGA) (Iyer et al. 2019), TLBO (Rao and Saroj 2017) and SAMPE-JAYA (Rao and Saroj 2017) algorithm. The design of the STHE on the mentioned costs was considered: the capital investment (C_{inv}), annual operating cost (C_{annual}), energy cost (C_E) and total discounted operating cost (C_{total_disc}) (Caputo et al. 2008). The objective is to minimize the total cost (C_{total}). The mathematical formulation of the design and economic optimization of the STHE problem is adopted from ARGA (Iyer et al. 2019). The work comprehensively addresses all three cases of this problem.

The SHMS algorithm is successfully investigated for solving three cases of STHE problem. The following computational parameters are selected for SHMS algorithm based on preliminary trials: number of homes $H = 20$, number of snails $S = 10$ per home, and search space interval parameter $c = 0.98$. The performance from SHMS algorithm is compared with well-known nature inspired optimization algorithms such as GA, PSO, ABC, BBO, ITHS, I-ITHS, FFA, CI, TLBO, SAMPE-Jaya and ARGA. The result comparison of Case 1, Case 2 and Case 3 of STHE problem are presented in Tables 20, 21 and 22, respectively. The comparison tables illustrate the outstanding performance of the SHMS algorithm in Case 1

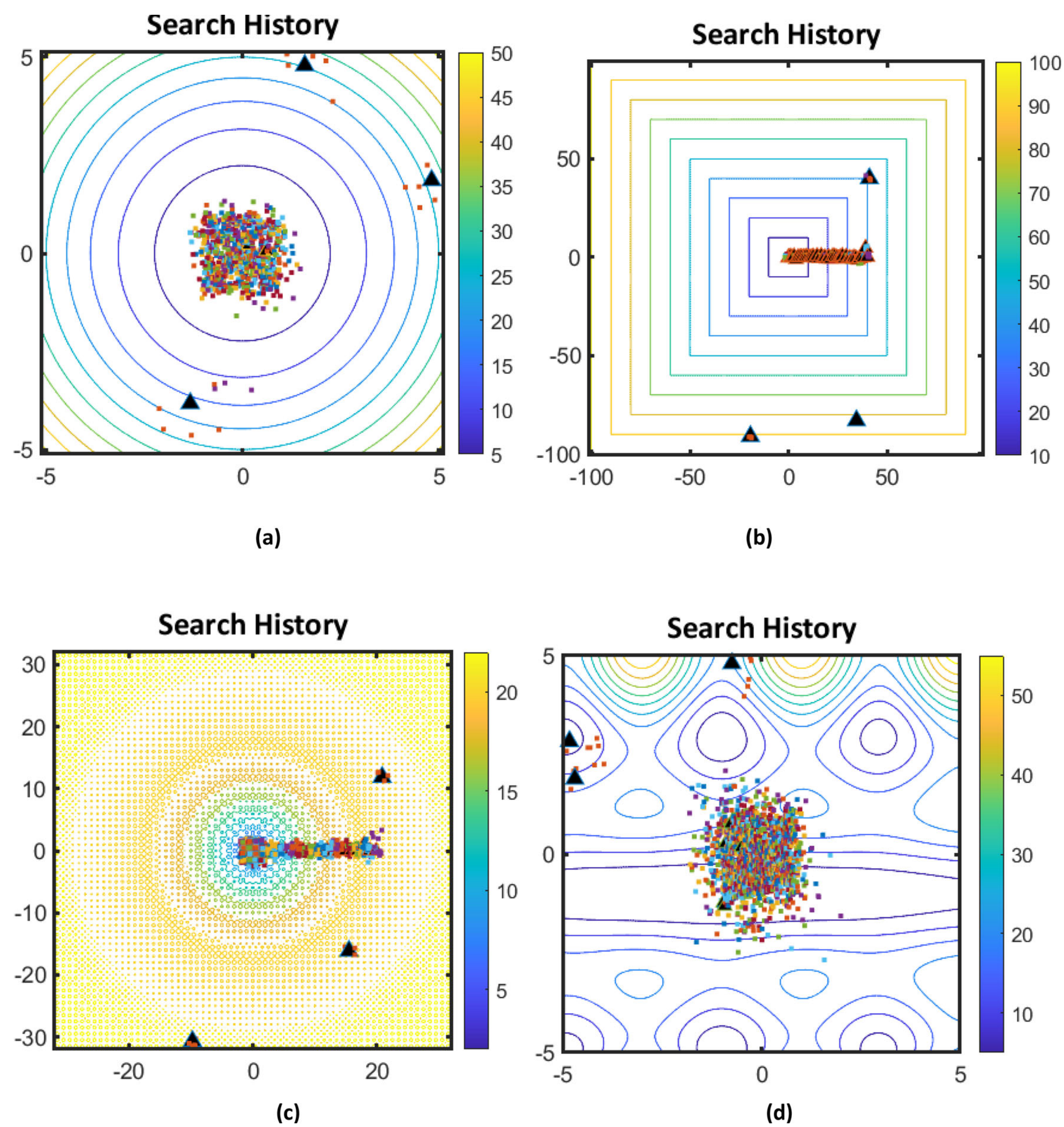


Fig. 5 The performance of SHMS algorithm representing the homes and associated snails. **a** Sphere function, **b** Schwefel 2.21 function, **c** Ackley function, **d** Penalized function

and Case 2 when compared with the other metaheuristic algorithms presented in Tables 20 and 21. However, in Case 3, the SHMS algorithm fell short of achieving a better solution when compared to the TLBO, SAMPLE-JAYA, I-ITHS, ITHS, BBO, and ABC algorithms. The cost comparison associated with these cases are presented in Figs. 6, 7 and 8, respectively. The SHMS algorithm is run for 30 times. The statistical results such as best, mean and worst function value, standard deviation, function evaluations and CPU time are presented in Table 23. The closeness to the best reported solution (%) is presented in Table 24. Snails are known for their ability to sense humidity gradients and move towards areas with higher humidity, which is vital for their survival. Similarly, in optimization algorithms, the idea is to mimic or draw inspiration from such natural processes to solve complex problems. The convergence plots for all the three cases obtained from the SHMS algorithm are presented in Figs. 9, 10 and 11.

For Case 1: Solving the case 1, the best, mean and worst function values (C_{total}) obtained from 30 trails are 41,718.6558, 41,725.3892 and 41,728.6558, respectively with standard deviation 4.0847, average function evaluations 20,510 and CPU time 9.62 s. The best solution

Table 9 Pairwise Wilcoxon signed rank test for benchmark functions (F1–13), with 30 dimensions

Other Algorithms vs SNAIL	p value	T +	T −	Winner
AVOA vs SNAIL	9.66E-01	32	34	**SHMS**
PSO vs SNAIL	1.05E-02	10	81	**SHMS**
GWO vs SNAIL	8.02E-01	41.5	49.5	**SHMS**
FFA vs SNAIL	9.42E-02	21	70	**SHMS**
WOA vs SNAIL	6.22E-01	32	46	**SHMS**
TLBO vs SNAIL	8.93E-01	43	48	**SHMS**
MFO vs SNAIL	1.34E-02	11	80	**SHMS**
BBO vs SNAIL	9.24E-02	21	70	**SHMS**
DE vs SNAIL	8.03E-02	20	71	**SHMS**
SSA vs SNAIL	2.15E-02	13	78	**SHMS**
GSA vs SNAIL	2.15E-02	13	78	**SHMS**
IPO vs SNAIL	1.27E-01	23	68	**SHMS**

Table 10 Pairwise Wilcoxon signed rank test for benchmark functions (F1–13), with 100 dimensions

Other Algorithms vs SNAIL	p value	T +	T-	Winner
AVOA vs SNAIL	1.34E-02	11	80	**SHMS**
PSO vs SNAIL	4.60E-03	7	84	**SHMS**
GWO vs SNAIL	2.15E-02	13	78	**SHMS**
FFA vs SNAIL	8.10E-03	9	82	**SHMS**
WOA vs SNAIL	1.02E-01	14	52	**SHMS**
TLBO vs SNAIL	1.75E-01	17	49	**SHMS**
MFO vs SNAIL	4.60E-03	7	84	**SHMS**
BBO vs SNAIL	1.71E-02	12	79	**SHMS**
DE vs SNAIL	8.10E-03	9	82	**SHMS**
SSA vs SNAIL	1.34E-02	11	80	**SHMS**
GSA vs SNAIL	6.10E-03	8	83	**SHMS**
IPO vs SNAIL	1.71E-02	12	79	**SHMS**

obtained using SHMS algorithm is 0.4649% better as compared to previously best reported solution using ARGA (Iyer et al. 2019) (refer Table 20).

For Case 2: The best mean worst function values (C_{total}) using SHMS algorithm for Case 2 are 19,084.3059, 19,088.3476 and 19,097.2054, respectively with standard deviation 3.1663, function evaluations 17,235 and CPU time 8.10 s. The best solution obtained using SHMS algorithm is 0.5952% better as compared to previously best reported solution using ARGA (Iyer et al. 2019) (refer Table 21).

For Case 3: The best mean worst function values (C_{total}) using SHMS algorithm for Case 3 are 20,744.3639 20,746.1280 and 20,749.8314, respectively with standard

Table 11 Pairwise Wilcoxon signed rank test for benchmark functions (F1–13), with 500 dimensions

Other Algorithms vs SNAIL	p value	T +	T −	Winner
AVOA vs SNAIL	7.65E-01	37	29	AVOA
PSO vs SNAIL	4.60E-03	7	84	**SHMS**
GWO vs SNAIL	1.71E-02	12	79	**SHMS**
FFA vs SNAIL	3.40E-03	6	85	**SHMS**
WOA vs SNAIL	2.78E-01	20	46	**SHMS**
TLBO vs SNAIL	4.65E-01	24	42	**SHMS**
MFO vs SNAIL	3.40E-03	6	85	**SHMS**
BBO vs SNAIL	8.10E-03	9	82	**SHMS**
DE vs SNAIL	4.60E-03	7	84	**SHMS**
SSA vs SNAIL	4.60E-03	7	84	**SHMS**
GSA vs SNAIL	2.40E-03	5	86	**SHMS**
IPO vs SNAIL	1.34E-02	11	80	**SHMS**

Table 12 Pairwise Wilcoxon signed rank test for benchmark functions (F1–13), with 1000 dimensions

Other Algorithms vs SNAIL	p value	T +	T −	Winner
AVOA vs SNAIL	7.65E-01	37	29	AVOA
PSO vs SNAIL	3.40E-03	6	85	**SHMS**
GWO vs SNAIL	1.71E-02	12	79	**SHMS**
FFA vs SNAIL	2.40E-03	5	86	**SHMS**
WOA vs SNAIL	2.78E-01	20	46	**SHMS**
TLBO vs SNAIL	2.04E-01	22	56	**SHMS**
MFO vs SNAIL	2.40E-03	5	86	**SHMS**
BBO vs SNAIL	3.40E-03	6	86	**SHMS**
DE vs SNAIL	2.40E-03	5	86	**SHMS**
SSA vs SNAIL	4.60E-03	7	84	**SHMS**
GSA vs SNAIL	2.40E-03	5	86	**SHMS**
IPO vs SNAIL	8.10E-03	9	82	**SHMS**

Table 13 Pairwise Wilcoxon signed rank test for benchmark functions (F14–23)

Other Algorithms vs SNAIL	p value	T +	T −	Winner
AVOA vs SNAIL	3.90E-03	45	0	AVOA
PSO vs SNAIL	3.91E-02	40	5	PSO
GWO vs SNAIL	7.80E-03	44	1	GWO
FFA vs SNAIL	3.90E-03	45	0	FFA
WOA vs SNAIL	3.90E-03	45	0	WOA
TLBO vs SNAIL	3.90E-03	45	0	TLBO
MFO vs SNAIL	3.90E-03	45	0	MFO
BBO vs SNAIL	7.80E-03	44	1	BBO
DE vs SNAIL	3.90E-03	45	0	DE
SSA vs SNAIL	7.80E-03	44	1	SSA
GSA vs SNAIL	7.80E-03	44	1	GSA
IPO vs SNAIL	3.90E-03	45	0	IPO

Table 14 Comparison of average running time results (sec.) over 30 runs for larger-scale problems with 1000 variables

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
F1	Best	9.17E-01	1.45E + 00	2.70E + 00	2.77E + 00	2.51E + 00	1.40E + 00	1.85E + 00	1.40E + 01	1.65E + 00	1.56E + 00	1.61E + 01	6.13E + 00	**1.38E-01**
	Worst	1.08E + 00	2.40E + 00	3.16E + 00	3.24E + 00	2.90E + 00	2.39E + 00	2.12E + 00	1.50E + 01	2.08E + 00	1.76E + 00	1.88E + 01	9.62E + 00	**1.69E-01**
	Mean	1.02E + 00	1.64E + 00	2.75E + 00	2.85E + 00	2.74E + 00	1.63E + 00	1.93E + 00	1.42E + 01	1.73E + 00	1.63E + 00	1.64E + 01	6.73E + 00	**1.45E-01**
	STD	7.82E-02	2.19E-01	9.87E-02	1.31E-01	1.08E-01	2.14E-01	6.81E-02	1.48E-01	1.12E-01	4.87E-02	6.90E-01	6.83E-01	**7.26E-03**
F2	Best	9.92E-01	1.51E + 00	2.79E + 00	2.99E + 00	2.81E + 00	1.50E + 00	1.90E + 00	1.42E + 01	1.69E + 00	1.58E + 00	6.56E + 01	6.00E + 00	**8.43E-02**
	Worst	1.13E + 00	1.86E + 00	3.32E + 00	4.33E + 00	3.18E + 00	1.88E + 00	2.24E + 00	1.87E + 01	1.99E + 00	1.78E + 00	9.04E + 01	7.19E + 00	**9.66E-02**
	Mean	1.01E + 00	1.72E + 00	2.89E + 00	3.27E + 00	2.96E + 00	1.65E + 00	2.00E + 00	1.46E + 01	1.89E + 00	1.62E + 00	7.30E + 01	6.51E + 00	**9.03E-02**
	STD	4.36E-02	1.01E-01	1.04E-01	3.16E-01	9.40E-02	8.26E-02	8.58E-02	8.72E-01	8.18E-02	4.77E-02	7.88E + 00	2.70E-01	**3.88E-03**
F3	Best	2.40E + 01	3.02E + 01	3.05E + 01	5.43E + 01	3.06E + 01	5.53E + 01	2.84E + 01	5.85E + 01	2.96E + 01	2.82E + 01	3.94E + 01	2.19E + 01	**1.26E + 00**
	Worst	2.54E + 01	3.66E + 01	3.71E + 01	5.95E + 01	3.50E + 01	6.07E + 01	2.98E + 01	5.93E + 01	3.35E + 01	3.00E + 01	4.19E + 01	3.90E + 01	**1.68E + 00**
	Mean	2.41E + 01	3.10E + 01	3.10E + 01	5.47E + 01	3.13E + 01	5.60E + 01	2.89E + 01	5.86E + 01	3.01E + 01	2.84E + 01	3.97E + 01	2.95E + 01	**1.50E + 00**
	STD	3.34E-01	1.49E + 00	1.45E + 00	1.11E + 00	9.16E-01	1.03E + 00	2.16E-01	3.10E-01	8.12E-01	3.33E-01	6.33E-01	5.66E + 00	**1.15E-01**
F4	Best	8.99E-01	1.42E + 00	2.74E + 00	2.63E + 00	2.82E + 00	1.35E + 00	1.82E + 00	1.40E + 01	1.71E + 00	1.54E + 00	1.61E + 01	6.03E + 00	**7.72E-01**
	Worst	1.07E + 00	2.44E + 00	3.25E + 00	3.27E + 00	3.82E + 00	2.13E + 00	2.00E + 00	1.64E + 01	2.23E + 00	1.71E + 00	1.98E + 01	6.64E + 00	**1.12E + 00**
	Mean	9.56E-01	1.69E + 00	2.86E + 00	2.84E + 00	3.04E + 00	1.47E + 00	1.89E + 00	1.43E + 01	1.89E + 00	1.59E + 00	1.64E + 01	6.45E + 00	**9.81E-01**
	STD	3.88E-02	2.00E-01	1.00E-01	1.47E-01	2.05E-01	1.77E-01	5.74E-02	5.73E-01	1.45E-01	4.92E-02	9.44E-01	2.02E-01	**8.36E-02**
F5	Best	9.97E-01	1.76E + 00	2.80E + 00	2.84E + 00	2.88E + 00	1.54E + 00	1.91E + 00	1.40E + 01	1.64E + 00	1.66E + 00	1.62E + 01	6.32E + 00	**7.76E-01**
	Worst	1.19E + 00	2.09E + 00	4.97E + 00	3.33E + 00	3.71E + 00	2.12E + 00	2.09E + 00	1.56E + 01	2.32E + 00	1.87E + 00	2.14E + 01	6.87E + 00	**9.10E-01**
	Mean	1.03E + 00	1.91E + 00	3.10E + 00	3.03E + 00	3.21E + 00	1.75E + 00	1.97E + 00	1.42E + 01	1.91E + 00	1.74E + 00	1.66E + 01	6.72E + 00	**8.19E-01**
	STD	4.27E-02	1.06E-01	4.31E-01	9.62E-02	1.90E-01	1.68E-01	6.04E-02	3.38E-01	1.57E-01	5.85E-02	1.34E + 00	9.59E-02	**3.17E-02**
F6	Best	9.38E-01	1.45E + 00	2.73E + 00	2.74E + 00	2.94E + 00	1.34E + 00	1.83E + 00	1.41E + 01	1.69E + 00	1.62E + 00	1.61E + 01	5.89E + 00	**9.65E-02**
	Worst	1.11E + 00	2.02E + 00	3.46E + 00	3.17E + 00	3.77E + 00	1.96E + 00	2.00E + 00	1.51E + 01	2.21E + 00	1.90E + 00	1.93E + 01	6.58E + 00	**1.16E-01**
	Mean	9.74E-01	1.76E + 00	2.88E + 00	2.88E + 00	3.14E + 00	1.52E + 00	1.90E + 00	1.43E + 01	1.91E + 00	1.70E + 00	1.67E + 01	6.36E + 00	**1.03E-01**
	STD	3.80E-02	1.29E-01	1.82E-01	9.69E-02	1.58E-01	1.60E-01	5.20E-02	1.33E-01	1.34E-01	6.84E-02	1.03E + 00	1.45E-01	**3.68E-03**
F7	Best	2.94E + 00	3.97E + 00	5.20E + 00	7.25E + 00	5.08E + 00	6.17E + 00	4.21E + 00	1.51E + 01	4.06E + 00	3.97E + 00	1.82E + 01	7.24E + 00	**9.05E-02**
	Worst	3.41E + 00	4.54E + 00	5.52E + 00	7.75E + 00	6.75E + 00	6.56E + 00	4.51E + 00	1.65E + 01	4.37E + 00	4.27E + 00	2.60E + 01	1.03E + 01	**1.79E-01**
	Mean	3.05E + 00	4.07E + 00	5.27E + 00	7.37E + 00	5.37E + 00	6.24E + 00	4.25E + 00	1.55E + 01	4.12E + 00	4.02E + 00	2.01E + 01	7.86E + 00	**1.08E-01**
	STD	1.11E-01	1.88E-01	8.60E-02	1.25E-01	3.59E-01	8.83E-02	6.89E-02	3.20E-01	8.51E-02	6.51E-02	3.27E + 00	6.37E-01	**1.79E-02**
F8	Best	1.26E + 00	2.45E + 00	3.17E + 00	3.89E + 00	3.33E + 00	2.51E + 00	2.28E + 00	1.50E + 01	2.60E + 00	2.19E + 00	2.38E + 01	6.12E + 00	**9.65E-02**
	Worst	1.77E + 00	3.51E + 00	3.74E + 00	4.71E + 00	3.92E + 00	3.19E + 00	2.77E + 00	1.59E + 01	3.64E + 00	2.54E + 00	2.88E + 01	6.94E + 00	**1.16E-01**
	Mean	1.35E + 00	2.71E + 00	3.23E + 00	4.25E + 00	3.59E + 00	2.78E + 00	2.41E + 00	1.52E + 01	2.82E + 00	2.32E + 00	2.45E + 01	6.62E + 00	**1.03E-01**
	STD	1.19E-01	1.84E-01	1.08E-01	1.68E-01	1.38E-01	1.72E-01	1.13E-01	2.54E-01	2.25E-01	7.37E-02	1.34E + 00	1.57E-01	**3.68E-03**
F9	Best	1.02E + 00	2.26E + 00	2.93E + 00	3.72E + 00	3.05E + 00	1.88E + 00	2.18E + 00	1.45E + 01	2.53E + 00	2.03E + 00	1.63E + 01	6.25E + 00	**2.73E-01**
	Worst	1.26E + 00	3.00E + 00	3.23E + 00	4.51E + 00	3.68E + 00	2.58E + 00	2.67E + 00	1.55E + 01	2.89E + 00	2.31E + 00	2.38E + 01	9.95E + 00	**3.48E-01**
	Mean	1.07E + 00	2.48E + 00	3.00E + 00	4.02E + 00	3.29E + 00	2.17E + 00	2.28E + 00	1.50E + 01	2.62E + 00	2.13E + 00	1.91E + 01	6.87E + 00	**3.00E-01**
	STD	4.70E-02	1.56E-01	7.73E-02	2.07E-01	1.41E-01	1.78E-01	9.77E-02	1.69E-01	6.92E-02	7.15E-02	3.54E + 00	6.97E-01	**2.03E-02**
F10	Best	1.07E + 00	2.10E + 00	2.98E + 00	3.75E + 00	3.05E + 00	1.96E + 00	2.26E + 00	1.46E + 01	2.58E + 00	2.08E + 00	1.64E + 01	4.77E + 00	**1.22E-01**
	Worst	1.54E + 00	2.77E + 00	3.27E + 00	4.86E + 00	3.69E + 00	2.61E + 00	2.52E + 00	1.56E + 01	3.12E + 00	2.35E + 00	1.95E + 01	5.42E + 00	**1.51E-01**
	Mean	1.16E + 00	2.34E + 00	3.01E + 00	4.00E + 00	3.31E + 00	2.24E + 00	2.32E + 00	1.50E + 01	2.74E + 00	2.18E + 00	1.66E + 01	4.95E + 00	**1.33E-01**
	STD	9.40E-02	1.90E-01	8.05E-02	2.43E-01	1.32E-01	1.88E-01	5.85E-02	2.08E-01	1.34E-01	7.08E-02	7.95E-01	1.09E-01	**6.94E-03**

Table 14 (continued)

No		AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	SHMS
F11	Best	1.23E + 00	2.27E + 00	3.10E + 00	4.16E + 00	3.27E + 00	2.24E + 00	2.38E + 00	1.46E + 01	2.81E + 00	2.25E + 00	1.66E + 01	6.52E + 00	**8.38E-02**
	Worst	1.56E + 00	3.50E + 00	3.70E + 00	5.20E + 00	4.40E + 00	2.91E + 00	2.69E + 00	1.55E + 01	3.26E + 00	2.53E + 00	1.73E + 01	1.03E + 01	**1.05E-01**
	Mean	1.29E + 00	2.60E + 00	3.21E + 00	4.42E + 00	3.51E + 00	2.48E + 00	2.49E + 00	1.50E + 01	2.92E + 00	2.35E + 00	1.67E + 01	7.19E + 00	**9.31E-02**
	STD	8.44E-02	2.20E-01	1.45E-01	2.19E-01	2.00E-01	1.76E-01	7.97E-02	2.29E-01	1.14E-01	6.92E-02	1.69E-01	6.23E-01	**4.97E-03**
F12	Best	3.62E + 00	5.27E + 00	6.16E + 00	9.41E + 00	6.24E + 00	8.40E + 00	5.24E + 00	1.53E + 01	5.66E + 00	5.00E + 00	1.89E + 01	8.98E + 00	**8.38E-02**
	Worst	4.41E + 00	6.35E + 00	6.68E + 00	1.02E + 01	6.66E + 00	9.02E + 00	5.63E + 00	2.12E + 01	6.17E + 00	5.47E + 00	2.23E + 01	9.70E + 00	**1.05E-01**
	Mean	3.76E + 00	5.44E + 00	6.29E + 00	9.80E + 00	6.39E + 00	8.54E + 00	5.31E + 00	1.58E + 01	5.79E + 00	5.09E + 00	1.94E + 01	9.45E + 00	**9.31E-02**
	STD	1.83E-01	2.55E-01	1.35E-01	1.49E-01	9.46E-02	1.24E-01	8.54E-02	1.01E + 00	1.20E-01	9.87E-02	9.67E-01	1.19E-01	**4.97E-03**
F13	Best	3.62E + 00	5.33E + 00	6.09E + 00	9.33E + 00	6.18E + 00	7.96E + 00	5.18E + 00	1.54E + 01	5.51E + 00	5.09E + 00	1.90E + 01	9.90E + 00	**2.65E-01**
	Worst	4.42E + 00	6.37E + 00	6.73E + 00	1.00E + 01	6.83E + 00	8.49E + 00	5.67E + 00	1.65E + 01	6.40E + 00	5.50E + 00	1.93E + 01	1.07E + 01	**2.99E-01**
	Mean	3.77E + 00	5.48E + 00	6.20E + 00	9.68E + 00	6.41E + 00	8.15E + 00	5.27E + 00	1.58E + 01	5.82E + 00	5.19E + 00	1.91E + 01	1.01E + 01	**2.80E-01**
	STD	1.96E-01	2.54E-01	1.24E-01	1.66E-01	1.27E-01	1.22E-01	1.04E-01	2.07E-01	2.07E-01	9.25E-02	7.58E-02	1.33E-01	**1.30E-02**

The bold values refers to the solution obtained by proposed SHMS algorithm

deviation 1.45653.1663, function evaluations 44,721 and CPU time 20.13 s. The best solution obtained using SHMS algorithm is 0.2775% better as compared to previously best reported solution using ARGA (Iyer et al. 2019) (refer Table 22).

SHMS algorithm has indeed demonstrated superior performance compared to other metaheuristic algorithms for solving the STHE design and economic optimization problem. It is due to its ability to efficiently navigate through the solution space, guided by the principles of cue following observed in snails. This makes it particularly effective in solving problems that involve multivariable and complex nature.

6 Conclusion and future directions

In this paper, a novel Snail Homing and Mating Search (SHMS) algorithm inspired from the living habitat of the snails is proposed. Snails usually live in moist and humid regions and continuously travel to find food and a mate, leaving behind a trail of mucus that serves as a guide for their return journey. Snails tend to navigate by following the available trails on the ground and responding to cues from nearby shelter homes. The approach is validated by solving set of benchmark problems consisting of 2 different groups of unimodal (UM) and multi-modal (MM) functions (F1–F23). To check the SHMS algorithms scalability, F1–F13 problems are solved for 30, 100, 500 and 1000 dimensions. Wilcoxon and Friedman statistical tests are conducted for comparing the performance of the SHMS algorithm with the existing algorithms. The performance of SHMS algorithm is exceedingly better as compared to PSO, GWO, FFA, WOA, TLBO, MFO, BBO, DE, SSA, GSA and IPO while solving F1–F13 functions for 30, 100, 500 and 1000 dimensions in terms of objective function value (best and mean), robustness, as well as computational time. The performance of the SHMS algorithm is marginally better as compared to AVOA for 30 and 100 dimensions. The solution quality highlighted that the SHMS algorithm is a robust approach with reasonable computational cost and could quickly reach in the close neighbourhood of the global optimum solution. For fixed dimensions F14–F23 functions SHMS algorithm could not yield better solutions as compared to other algorithms due to weak exploitation. In addition, real-world application of SHMS algorithm is successfully demonstrated in the engineering design domain by solving three cases of the STHE problem. The total cost (C_{total}) is significantly

Table 15 Friedmann test for benchmark functions (F1–F13), with 30 dimensions

Algorithm	AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
Mean Values	2.5	11.6923	5.2308	7.3077	5.8462	3.6923	11.5385	7.7692	7.5385	8.6154	8.7692	7.2308	**3.2692**
Ranking	1	13	4	7	5	3	12	9	8	10	11	6	**2**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 16 Friedmann test for benchmark functions (F1–F13), with 100 dimensions

Algorithm	AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
Mean Values	1.8462	10.6923	4.8462	10.4615	4.3846	3.5385	11.7692	6.4615	10.7692	8.2308	8.6923	6.8462	**2.4615**
Ranking	1	11	5	10	4	3	13	6	12	8	9	7	**2**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 17 Friedmann test for benchmark functions (F1–F13), with 500 dimensions

Algorithm	AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
Mean Values	1.7692	8.7692	5.2308	11.0385	4.1538	3.6923	11.8462	7.9231	11.3462	7.6154	8.2308	6.6923	**2.6923**
Ranking	1	10	5	11	4	3	13	8	12	7	9	6	**2**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 18 Friedmann test for benchmark functions (F1–F13), with 1000 dimensions

Algorithm	AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
Mean Values	1.7308	8.0385	5	10.9615	4.0385	4.3077	11.4231	9.5385	11.8077	7.5769	7.5385	6.3846	**2.6538**
Ranking	1	9	5	11	3	4	12	10	13	8	7	6	**2**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 19 Friedmann test for benchmark functions (F14–F23)

Algorithm	AVOA	PSO	GWO	FFA	WOA	TLBO	MFO	BBO	DE	SSA	GSA	IPO	**SHMS**
Mean Values	13.35	11.6	6.15	5.05	7.7	5.1	7.25	9.65	4.7	7	6.45	5.2	**11.8**
Ranking	13	11	5	4	9	2	8	10	1	7	6	3	**12**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 20 Comparison of SHMS results Design and Economic Optimization of STHE Problem Case 1

Parameters	Original Study	GA	PSO	ABC	BBO	ITHS	I-ITHS	CI	FFA	TLBO	SAMPE-Jaya	ARGA	SHMS
D_s(m)	0.8940	0.8300	0.8100	1.3905	0.8010	0.7620	0.7635	0.7800	0.8580	0.8580	0.7686	0.6651	**0.6447**
L(m)	4.8300	3.3790	3.1150	3.9630	2.0400	2.0791	2.0391	1.9367	2.4160	2.4160	1.4766	1.2636	**1.1121**
b(m)	0.3560	0.5000	0.4240	0.4669	0.5000	0.4988	0.4955	0.5000	0.4020	0.4020	0.4999	0.4903	**0.4166**
d_o(m)	0.0200	0.0160	0.0150	0.0104	0.0100	0.0101	0.01	0.0100	0.0157	0.0157	0.0100	0.0100	**0.0100**
P_t(m)	0.0250	0.0200	0.0187	–	0.0125	0.1264	0.0125	0.0125	0.0197	0.0196	0.0125	0.0125	**0.0125**
C_1(m)	0.0050	0.0040	0.0037	–	0.0025	0.0253	0.0025	0.0025	–	–	–	0.0025	**0.0025**
n_t	2	2	2	2	2	2	2	2	2	–	–	2	**2**
N_t	918	1567	1658	1528	3587	3454	3558	3734.1233	1692	1692	3614	2625.8730	**2451.7768**
v_t(m/s)	0.7500	0.6900	0.6700	0.3600	0.7700	0.7820	0.7744	0.7381	0.6560	0.6560	0.7624	1.0492	**1.1237**
Re_t	14,925	10,936	10,503	–	7642.4900	7842.5200	7701.2900	7342.7474	10,286	10,286	7586.5700	10,440.1200	**11,181.4577**
Pr_t	5.7000	5.7000	5.7000	–	5.7000	5.7000	5.700	5.6949	5.7000	5.7000	5.7000	5.6949	**5.6949**
h_t(W/m^{2}K)	3812	3762	3721	3818	4314	4415.9180	4388.7900	4584.7085	6228	6228	3777.8800	6196.0020	**6545.5440**
f_t	0.0280	0.0310	0.0311	–	0.0340	0.0354	0.0355	0.0343	0.0312	0.0312	0.0340	0.0310	**0.0305**
ΔP_t(Pa)	6251	4298	4171	3043	6156	6998.7000	6887.6300	5862.7287	4246	4246	5078.3700	9756.2380	**10,349.6306**
a_s(m^2)	0.0320	0.0830	0.0687	–	0.0801	0.0760	0.0757	0.0780	–	–	–	0.0652	**0.0537**
D_e(m)	0.0140	0.0110	0.0107	–	0.0070	0.0072	0.0071	0.0071	0.0105	0.0105	0.0071	0.0071	**0.0071**
v_s(m/s)	0.5800	0.4400	0.5300	0.1180	0.4600	0.4875	0.4898	0.4752	0.5400	0.54	0.4822	0.5683	**0.6899**
Re_s	18,381	11,075	12,678	–	7254	7736.8900	7684.0540	7451.3906	12,625	12,625	7571.3400	8912.3250	**10,819.8036**
Pr_s	5.1000	5.1000	5.1000	–	5.1000	5.0821	5.0822	5.0821	5.1000	5.1000	5.1000	5.0821	**5.0821**
h_s(W/m^{2}K)	1573	1740	1950.8000	3396	2197	2213.8900	2230.9130	2195.9461	1991	1991	2084.0500	2422.8040	**2695.5285**
f_s	0.3300	0.357	0.3490	–	0.3790	0.3759	0.3762	0.3780	0.3490	0.349	0.3771	0.3680	**0.3575**
ΔP_s(Pa)	35,789	13,267	20,551	8390	13,799	14,794.9400	14,953.9100	13,608.4472	18,788	18,788	10,488.3900	10,746.3100	**15,447.1357**
U(W/m^{2}K)	615	660	713.9000	832	755	760.5940	761.5780	764.5084	876.4000	876.4000	719.0500	1031.4720	**1090.5668**
S(m^2)	278.6000	262.8000	243.2000	–	229.9500	228.3200	228.0300	227.1607	202.3000	202.3000	167.5600	168.2758	**159.1575**
C_{inv}(€)	51,507	49,259	46,453	44,559	44,536	44,301.6600	44,259.0100	44,132.5190	39,336	39,336	37,519.8900	35,498.8700	**34,139.5254**
$C_{annual}(eur/year)$	21,111	947	1038.7000	1014.5000	984	964.1640	962.4858	955.9112	1040	1040	731.7100	1043.9600	**1233.4685**
C_{total_disc}(€)	12,973	5818	6778.2000	6233.8000	6046	5924.343	5914.058	5873.6607	6446	6446	4496.08	6414.68	**7579.1304**
C_{total}(€)	64,480	55,077	53,231	50,793	50,582	50,226	50,173	50,006.1797	45,782	45,782	42,015.98	41,913.54	**41,718.6558**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 21 Comparison of SHMS results Design and Economic Optimization of STHE Problem Case 2

Parameters	Original Study	GA	PSO	ABC	BBO	ITHS	I-ITHS	CI	FFA	ARGA	SHMS
D_s(m)	0.5390	0.6300	0.5900	0.3293	0.74	0.32079	0.31619	0.4580	0.7276	0.4000	**0.4000**
L(m)	4.8800	2.1530	1.5600	3.6468	1.199	5.15184	5.06235	1.3833	1.6400	0.7100	**0.6900**
b(m)	0.1270	0.1200	0.1112	0.0924	0.1066	0.24725	0.24147	0.1250	0.1054	0.1546	**0.1526**
d_o(m)	0.0250	0.0200	0.0150	0.0105	0.015	0.01204	0.01171	0.0100	0.0157	0.0114	**0.0114**
P_t(m)	0.0310	0.0250	0.0187	–	0.0188	0.01505	0.01464	0.0125	0.0197	0.0143	**0.0143**
C_1(m)	0.0060	0.0050	0.0037	–	0.0038	0.00301	0.00293	0.0025		0.0028	**0.0028**
n_t	4	4	2	2	2	1	1	2		2	**2**
N_t	158	391	646	511	1061	301	309	1152.888	924	635.2294	**635.2587**
v_t(m/s)	1.4400	0.8700	0.9300	0.4300	0.69	0.8615	0.8871	0.6522	0.6770	0.9041	**0.9041**
Re_t	8227	4068	3283	–	2298	2306.7700	2303.4600	1450.0174	2408	2299.9900	**2299.9910**
Pr_t	55.2000	55.2000	55.2000	–	55.2	56.4538	56.4538	56.4538	55.2000	56.4538	**56.4538**
h_t(W/m^{2}K)	619	1168	1205	2186	1251	1398.8500	1435.6800	1639.2213	1262	1174.5700	**1208.7230**
f_t	0.0330	1168	0.0440	–	0.05	0.0485	0.0485	0.0591	0.0490	0.0498	**0.0498**
ΔP_t(Pa)	49,245	14,009	16,926	1696	5109	10,502.4500	11,165.4500	5382.9311	9374	5179.4140	**5091.2730**
a_s(m^2)	0.0137	0.0148	0.0131	–	0.0158	0.0158	0.0153	0.0114		0.0124	**0.0122**
D_e(m)	0.0250	0.0190	0.0149	–	0.0149	0.0118	0.0116	0.0071	0.0156	0.0081	**0.0081**
v_s(m/s)	0.4700	0.4300	0.4950	0.3700	0.432	0.4095	0.4253	0.5672	0.4000	0.5249	**0.5316**
Re_s	25,281	18,327	15,844	–	13,689	10,345.2900	10,456.3900	8568.0357	14,448	9073.6440	**9188.7850**
Pr_s	7.5	7.5	7.5	–	7.5	7.6	7.6	7.6	7.5	7.6	**7.6**
h_s(W/m^{2}K)	920	1034	1288	868	1278	1248.8600	1290.7890	2062.1966	1156	1857.5760	**1870.5850**
f_s	0.3150	0.331	0.3370	–	0.345	0.3598	0.3593	0.3702	0.3422	0.3670	**0.3663**
ΔP_s(Pa)	24,909	15,717	21,745	10,667	15,275	14,414.2600	15,820.7400	36,090.0964	12,768	9708.0010	**9780.7940**
U(W/m^{2}K)	317	376	409.3000	323	317.75	326.0710	331.3580	381.6827	347.6000	336.1286	**339.9925**
S(m^2)	61.5000	52.9000	47.5000	61.5660	60.35	58.6410	57.7050	50.0970	56.6000	56.84084	**56.1948**
C_{inv}(€)	19,007	17,599	16,707	19,014	18,799	18,536.5500	18,383.4600	17,129.8543	18,202	18,241.7900	**18,135.8200**
$C_{annual}(eur/year)$	1304	440	523.3000	197.1390	164.414	272.5760	292.7937	352.885	210.2000	155.7100	**154.3616**
C_{total_disc}(€)	8012	2704	3215.6000	1211.3000	1010.25000	1674.8600	1799.0900	2163.3257	1231	956.7900	**948.4850**
C_{total}(€)	27,020	20,303	19,922.6000	20,225	19,810	20,211	20,182	19,298.1800	19,433	19,198.5800	**19,084.3100**

The bold values refers to the solution obtained by proposed SHMS algorithm

Table 22 Comparison of SHMS results Design and Economic Optimization of STHE Problem Case 3

Parameters	Original Study	GA	PSO	ABC	BBO	ITHS	I-ITHS	CI	TLBO	SAMPE-Jaya	ARGA	SHMS
$D_s(m)$	0.3870	0.6200	0.0181	1.0024	0.5579	0.5726	0.5671	0.5235	0.5524	0.5671	0.4602	**0.4702**
$L(m)$	4.8800	1.5480	1.4500	2.4000	1.1330	0.9737	0.9761	1.1943	0.9854	0.9569	0.7938	**0.7054**
$b(m)$	0.3050	0.4400	0.4230	0.3540	0.5000	0.4974	0.4989	0.5000	0.4640	0.4990	0.4602	**0.5104**
$d_o(m)$	0.0190	0.0160	0.0145	0.1030	0.0100	0.0101	0.0100	0.0100	0.0100	0.0100	0.0119	**0.0100**
$P_t(m)$	0.0230	0.0200	0.0187	–	0.0125	0.0126	0.0125	0.0125	0.0125	0.0125	0.0149	**0.0125**
$C_1(m)$	0.0040	0.0040	0.0036	–	0.0025	0.0025	0.0025	0.0025			0.0029	**0.0025**
n_t	2	2	2	2	2	2	2	2			2	**2**
N_t	160	803	894	704	1565	1845	1846	1548.6665	1743	1841	781.7678	**1222.0030**
$v_t(m/s)$	1.7600	0.6800	0.7400	0.3600	0.8980	0.7470	0.7610	0.9083	0.80695	0.76399	1.2534	**1.1508**
Re_t	36,409	9487	9424	–	7804	6552	6614	7889.7151	7009.9800	6636.8200	13,043.0804	**9997.4150**
Pr_t	6.2000	6.2000	6.2000	–	6.2000	6.2000	6.2000	6.2026	6.2026	6.2025	6.2025	**6.2025**
$h_t(W/m^2K)$	6558	6043	5618	4438	9180	5441	5536	4901.7267			6290.1116	**6170.5740**
f_t	0.0230	0.0310	0.0314	–	0.0337	0.0369	0.0368	0.0336	0.034817	0.035386	0.0292	**0.0314**
$\Delta P_t(Pa)$	62,812	3673	4474	2046	4176	3869	4049	6200.0472	4416.4200	3926.0100	7719.0230	**6975.8420**
$a_s(m^2)$	0.0236	0.0541	0.0590	–	0.0558	0.0569	0.0565	0.0523	5789.1700	5541.3000	0.0423	**0.0480**
$D_e(m)$	0.0130	0.0150	0.0100	–	0.0071	0.0071	0.0071	0.0071	0.00711	0.0071	0.0085	**0.0071**
$v_s(m/s)$	0.9400	0.4100	0.375	0.1200	0.3980	0.3893	0.3919	0.4237	0.4326	0.3917	0.5236	**0.4620**
Re_s	16,200	8039	4814	–	3515	3473	3461	3746.0280	3830.5270	3467.8390	5547.5447	**4085.1680**
Pr_s	5.4000	5.4000	5.4000	–	5.4000	5.4000	5.4000	5.3935	5.3935	5.3935	5.3935	**5.3935**
$h_s(W/m^2K)$	5735	3476	4088.3000	5608	4911	4832	4871	5078.1022	5374.5600	5088.4280	5267.2957	**5333.3460**
f_s	0.3370	0.3740	0.403	–	0.4230	0.4238	0.4241	0.4191	0.4177	0.4239	0.3951	**0.4136**
$\Delta P_s(Pa)$	67,684	4365	4271	27,166	5917	4995	5062	6585.2425	6412.9500	4928.0720	5024.0673	**4016.2380**
$U\ (W/m^2K)$	1471	1121	1177	1187	1384	1220	1229	1198.4141	1274.7300	1242.8400	1296.8901	**1294.3750**
$S\ (m^2)$	46.6000	62.5000	59.2000	54.7200	55.7300	57.3000	56.6400	58.0975	53.9355	55.3180	59.4877	**59.6033**
$C_{inv}(€)$	16,549	19,163	18,614	17,893	18,059	18,273	18,209	18,447.6373	17,764.3000	17,991.9600	18,674.9100	**18,693.7960**
$C_{annual}(eur/year)$	4466	272	276	257.8200	203.6800	231	238	383.4699	278.4550	231.5300	346.1900	**333.7221**
$C_{total\_disc}(€)$	27,440	1671	1696	1584.2000	1251.5000	1419	1464	2356.2566	1710.9880	1422.6900	2127.1800	**2050.5779**
$C_{total}(€)$	43,989	20,834	20,310	19,478	19,310	19,693	19,674	20,803.8940	19,475.2970	19,414.6500	20,802.0900	**20,744.3639**

The bold values refers to the solution obtained by proposed SHMS algorithm

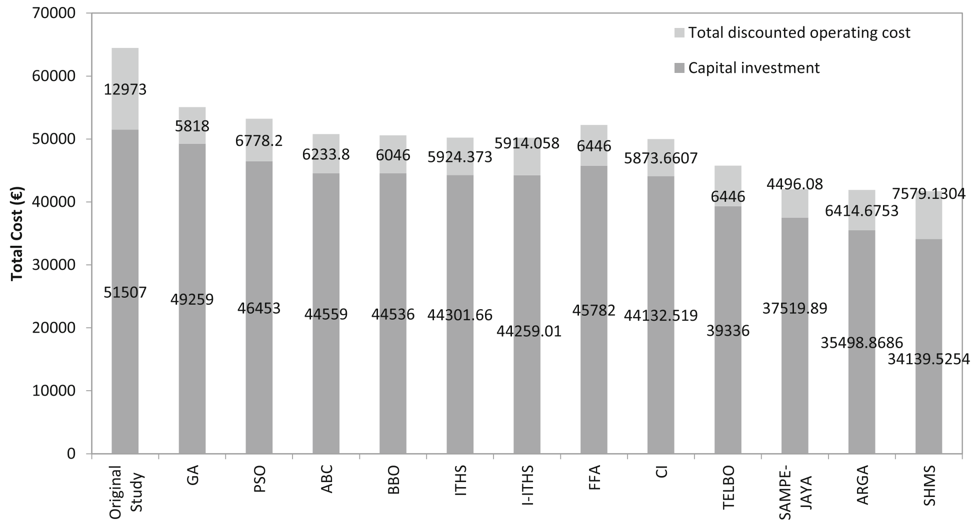


Fig. 6 Total Cost Comparison for Case 1

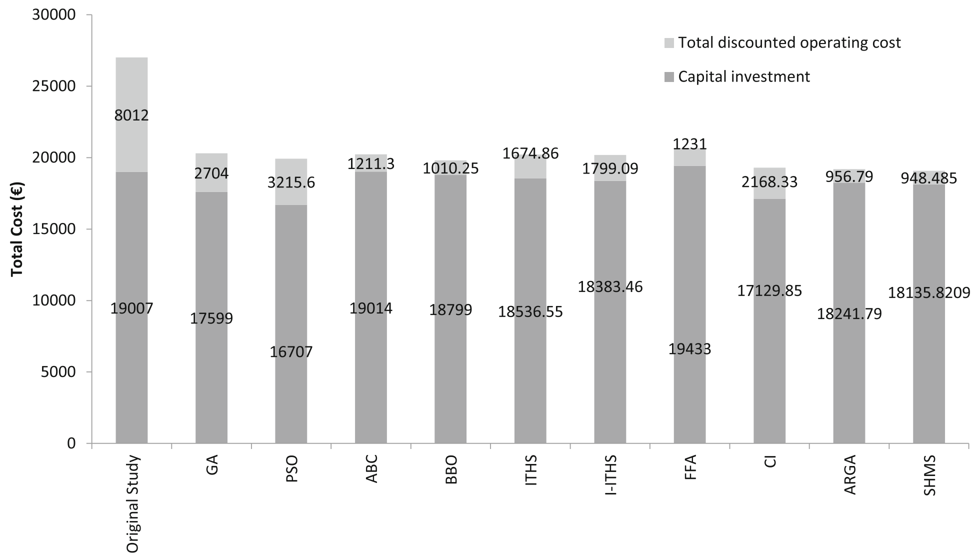


Fig. 7 Total Cost Comparison for Case 2

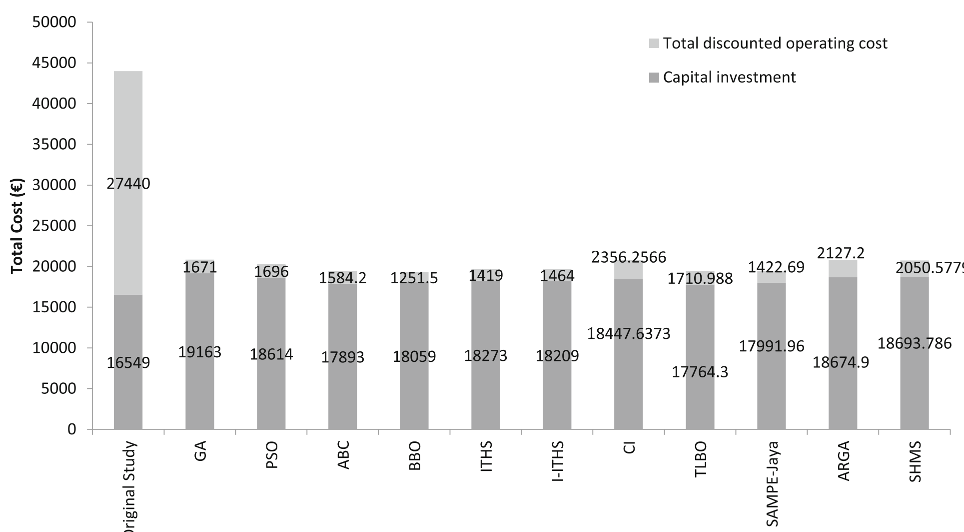


Fig. 8 Total Cost Comparison for Case 3

Table 23 SHMS performance details

Case studies	Solutions Best Mean Worst	Standard Deviation	Avg. No. of Function Evaluations (FE)	Avg. Comp. Time(sec)
Case 1	41,718.6558 41,725.3892 41,728.6558	4.0847	20,510	9.62
Case 2	19,084.3059 19,088.3476 19,097.2054	3.1663	17,235	8.10
Case 3	20,744.3639 20,746.1280 20,749.8314	1.4565	44,721	20.13

Table 24 Closeness of SHMS solutions with other algorithms

Case studies	Referred algorithms	Solutions of Total Cost (€)	Closeness to the Best Reported Solution (%)
Case 1	Original Study	64,480	**35.2998** ↑
	GA	55,077	**24.2539** ↑
	PSO	53,231.1	**21.6272** ↑
	ABC	50,793	**17.8653** ↑
	BBO	50,582	**17.5227** ↑
	ITHS	50,226	**16.9381** ↑
	I-ITHS	50,173	**16.8503** ↑
	FFA	45,783	**8.8774** ↑
	CI	50,006.18	**16.5729** ↑
	TLBO	45,782	**8.8754** ↑
	SAMPE-Jaya	42,015.98	**0.7076** ↑
	ARGA	41,913.54	**0.4649** ↑
Case 2	Original Study	27,020	**29.3697** ↑
	GA	20,303	**6.0025** ↑
	PSO	19,922.6	**4.2077** ↑
	ABC	20,225	**5.6400** ↑
	BBO	19,810	**3.6632** ↑
	ITHS	20,211	**5.5746** ↑
	I-ITHS	20,182	**5.4389** ↑
	FFA	19,433	**1.7943** ↑
	CI	19,298.18	**1.1082** ↑
	ARGA	19,198.58	**0.5952** ↑
Case 3	Original Study	43,989	**52.8419** ↑
	GA	20,834	**0.4302** ↑
	PSO	20,310	2.1386 ↓
	ABC	19,478	6.5015 ↓
	BBO	19,310	7.4280 ↓
	ITHS	19,693	5.3387 ↓
	I-ITHS	19,674	5.4405 ↓
	CI	20,803.89	**0.2861** ↑
	TLBO	19,475.297	6.5162 ↓
	SAMPE-Jaya	19,414.65	6.8490 ↓
	ARGA	20,802.09	**0.2775** ↑

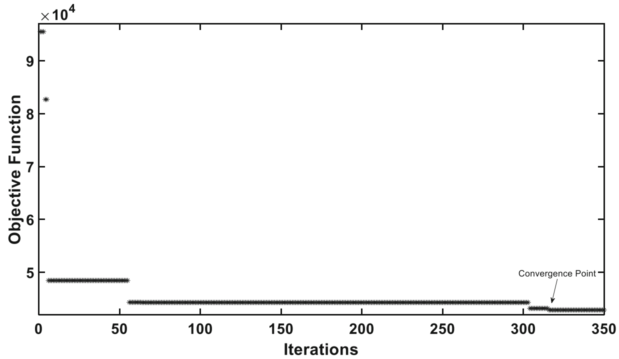


Fig. 9 Convergence plot for Design and Economic Optimization of STHE Problem Case 1

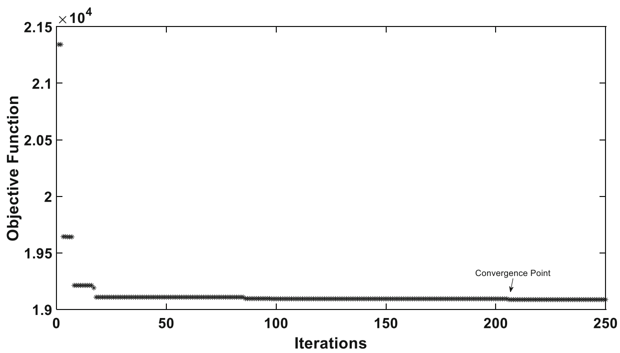


Fig. 10 Convergence plot for Design and Economic Optimization of STHE Problem Case 2

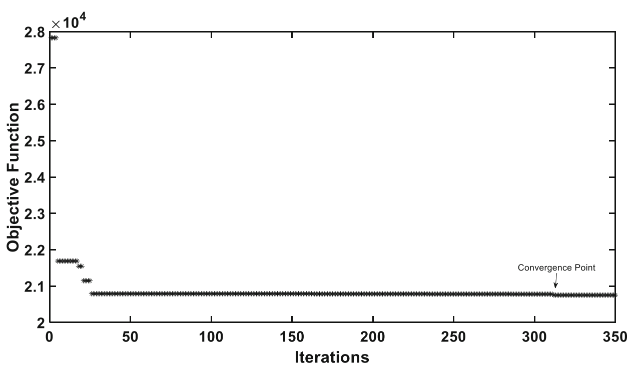


Fig. 11 Convergence plot for Design and Economic Optimization of STHE Problem Case 3

minimized. The results are compared with other well-known metaheuristic algorithms such as GA, PSO, ABC, BBO, ITHS, I-ITHS, FFA, CI, TLBO, SAMPE-Jaya and ARGA. There are certain limitations of the algorithm observed. They are as follows:

1. The computational cost increases as the number of snails increase. In the current version of the SHMS, the number of snails has been chosen based on the preliminary trials. In the future, an adaptive approach can be developed.
2. The snails are required to generate the position intervals in the close vicinity of their homes. This necessitates choosing an appropriate 'neighbourhood interval parameter 'c'. A hybrid approach needs to be developed so that the parameter can be approximated.
3. Every snail tends to follow the trails of the fertile snail in the search of food and shelter to improve its position/solution. However, there is a possibility to follow the trail of any of the nearby homes which may result in a worse solution. An improved mechanism needs to be developed which may help in biasing the solution for jumping out of the local optima.
4. Furthermore, a generalised constraint handling mechanism needs to be developed and incorporated into the SHMS algorithm. This can help SHMS algorithm to solve real-world problems which are inherently constrained in nature. The problems could be from the structural engineering and supply-chain management domain.

Appendix: SHMS Illustration

Sphere function with two variables:

Minimize $F = \sum_{i=1}^{2} x_i^2$

Subject to $-5.12 \le x_i \le 5.12,\ i = 1, 2$

The procedure of SHMS algorithm is discussed Sect. 3.1 is detailed below.

It includes the details of iterative calculation using SHMS algorithm. The computation parameter considered are as follows: number of homes $H = 3$, number of snails $S = 5$/home, neighborhood intervals parameter $c = 0.98$. The convergence plot of 20 iterations is presented in Fig. 12.

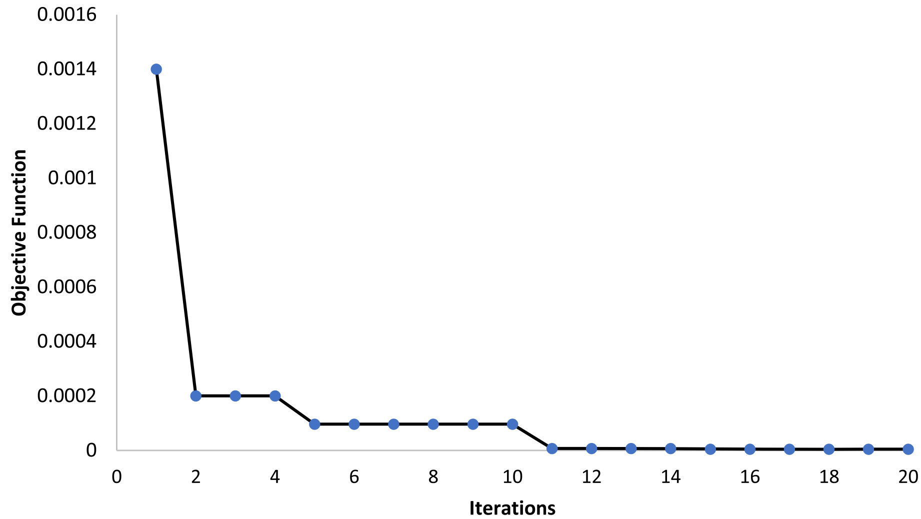


Fig. 12 Convergence Plot

Iteration 1

Step 1: Generation of Home and Snails

Equation 2: Initialize the positions of H homes

$\boldsymbol{X_H} = ((X_1), \ldots, (X_h), \ldots, (X_H))$

$$\begin{array}{c} \\ X_1 \\ X_2 \end{array} \begin{array}{c} \begin{array}{ccc} H_1 & H_2 & H_3 \end{array} \\ \begin{bmatrix} 3.9725 & 2.5926 & 3.0932 \\ -0.6000 & -4.3502 & -3.5406 \end{bmatrix} \end{array}$$

Equation 3: Generate the sampling interval of snails within the close neighborhood of position of homes.

$\psi_S = X_h \pm c$

$$\begin{array}{c} X_1 \\ X_2 \end{array} \left\{ \begin{array}{ccc} [2.9925, 4.9525] & [1.6126, 3.5726] & [2.1132, 4.0732] \\ [-1.5800, 0.3799] & [-5.1200, -3.3702] & [-4.5206, -2.5606] \end{array} \right\}$$

Equation 4: Every snail randomly generates the position

$$\begin{array}{c} H_1 \\ \begin{array}{cc} X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 3.4771 - 0.5442 \\ 3.1478 - 1.2052 \\ 4.6647 - 0.0908 \\ 3.3006 - 0.3746 \\ 4.2011 - 1.2819 \end{array} \right\} \end{array} \begin{array}{c} H_2 \\ \begin{array}{cc} X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 2.5037 - 4.1282 \\ 2.9495 - 3.9072 \\ 2.1639 - 3.4077 \\ 2.8373 - 3.5467 \\ 3.4584 - 3.9853 \end{array} \right\} \end{array} \begin{array}{c} H_3 \\ \begin{array}{cc} X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 4.0398 - 3.7018 \\ 2.4343 - 4.4132 \\ 3.1124 - 3.5031 \\ 3.3428 - 4.2570 \\ 3.6812 - 3.8014 \end{array} \right\} \end{array}$$

Equation 5: Calculate the function value

$$\begin{array}{c} H_1 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 12.3866 \\ 11.3613 \\ 21.7679 \\ 11.0343 \\ 19.2934 \end{array} \right\} \end{array} H_2 \begin{array}{c} H_2 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 23.3109 \\ 23.9661 \\ 16.2949 \\ 20.6301 \\ 27.8434 \end{array} \right\} \end{array} H_3 \begin{array}{c} H_3 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} \left\{ \begin{array}{c} 30.0238 \\ 25.4025 \\ 21.9596 \\ 29.2970 \\ 28.0026 \end{array} \right\} \end{array}$$

Step 2: Calculation of Fecundity Index of snails

If iteration = = 3

$$I_{s^h} = \left\| \frac{\left(f\left(X_1^h\right)^{iter} - f\left(X_1^h\right)^{iter-1}\right)}{\left(f\left(X_1^h\right)^{iter} - f\left(X_1^h\right)^{iter-2}\right)} \right\|$$

For first 2 iterations fecundity index I_{s^h} is randomly generated [0,1]

$$I_{s^h} = \begin{bmatrix} 0.5044 & 0.3082 & 0.7206 \\ 0.6550 & 0.7491 & 0.5687 \\ 0.0364 & 0.8520 & 0.2351 \\ 0.1939 & 0.0994 & 0.9106 \\ 0.7495 & 0.5978 & 0.9506 \end{bmatrix}$$

Step 3: Calculate the Probability and apply roulette wheel approach

Equation 7: $P_s = \frac{\left(1/f\left(X_s^h\right)\right)}{\sum_{s=1}^{S}\left(1/f\left(X_s^h\right)\right)}$ $(s = 1, \ldots, S)$

$$\begin{array}{cc} & H_1 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{c} 0.1040 \\ 0.1134 \\ 0.0592 \\ 0.1168 \\ 0.0668 \end{array} \right\} \end{array} \begin{array}{cc} & H_2 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{c} 0.0553 \\ 0.0537 \\ 0.0791 \\ 0.0624 \\ 0.0463 \end{array} \right\} \end{array} \begin{array}{cc} & H_3 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{c} 0.0429 \\ 0.0507 \\ 0.0587 \\ 0.0440 \\ 0.0460 \end{array} \right\} \end{array}$$

Step 5: Update the position of snails

Equation 10: $\mathrm{s}_{\mathrm{up}}^{\mathrm{h}} = \mathrm{LD}_{\mathrm{s}} \times \left(\mathrm{s}^{\mathrm{h}} - \mathrm{s}_{\mathrm{fecund}}^{\mathrm{h}}\right)$

$$\begin{array}{cc} & \begin{array}{cc} & H_1 \\ X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{cc} 0.5873 & 2.7561 \\ -1.4221 & -1.0447 \\ 0.1838 & 0.5933 \\ -0.0269 & 0.0258 \\ 0.1522 & 2.2815 \end{array} \right\} \end{array} \begin{array}{cc} & \begin{array}{cc} & H_2 \\ X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{cc} 0.0442 & 0.1816 \\ -0.1967 & -2.6807 \\ -0.6138 & 0.1267 \\ -0.3643 & 0.5119 \\ -0.0186 & -3.4157 \end{array} \right\} \end{array} \begin{array}{cc} & \begin{array}{cc} & H_3 \\ X_1 & X_2 \end{array} \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{cc} 0.8789 & -2.4601 \\ -0.7108 & -3.1960 \\ 0.0840 & 0.2082 \\ 1.1643 & -0.8387 \\ 0.8334 & -0.2515 \end{array} \right\} \end{array}$$

Step 4: Mating and Love Dart

Equation 8: $LD_s = \frac{1}{I_{s^h} \times \left(f\left(X_s^h\right) - f\left(X_{s_{fecund}}^h\right)\right)}$

$$LD_s = \begin{bmatrix} -0.2405 & -1.5513 & 0.0744 \\ -0.1491 & 0.1059 & 0.1252 \\ -4.5257 & -0.2707 & -2.1198 \\ -3.8145 & -1.1613 & 0.0845 \\ -0.1243 & 0.1082 & 0.1427 \end{bmatrix}$$

Normalized LD.
Equation 9:

$$LD_s = \begin{bmatrix} 0.9179 & 0.6371 & 0.9854 \\ 0.9375 & 0.9921 & 0.9963 \\ 0 & 0.9114 & 0.5154 \\ 0.1523 & 0.7207 & 0.9875 \\ 0.9428 & 0.9926 & 1.0000 \end{bmatrix}$$

Based on random integer number r the snails are assigned to homes.

$$\begin{array}{cc} & H_1 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \end{array} & \left\{ \begin{array}{c} 0.0014 \\ 5.2283 \\ 7.2249 \\ 0.3928 \\ 0.3947 \\ 10.7196 \\ 2.0590 \end{array} \right\} \end{array} \begin{array}{cc} & H_2 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \end{array} & \left\{ \begin{array}{c} 7.9408 \\ 0.0349 \\ 6.8247 \\ 0.0504 \\ 0.7578 \end{array} \right\} \end{array} \begin{array}{cc} & H_3 \\ \begin{array}{c} s_1 \\ s_2 \\ s_3 \end{array} & \left\{ \begin{array}{c} 3.1138 \\ 0.3857 \\ 11.6671 \end{array} \right\} \end{array}$$

Best Snail Solution from each Home.

$$\begin{array}{ccc} H_1 & H_2 & H_3 \end{array}$$
$$[0.0014 \quad 0.0349 \quad 0.3857]$$

Associated variable values are

$[-0.02690.0258]$ $[0.04420.1816]$ $[0.18380.5933]$

The variable values of minimum function value from each home are the new location of home.
Continue to Eq. 3

Iteration 2 Equation 3 $\begin{matrix} X_1 \\ X_2 \end{matrix}\left\{\begin{matrix} [-1.0069, 0.9531] & [-0.9358, 1.0242] & [-0.7962, 1.1638] \\ [-0.9542, 1.0058] & [-0.7984, 1.1616] & [-0.7962, 1.5733] \end{matrix}\right\}$	…	Equation 10 H_1 $\begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5\\ s_6\\ s_7 \end{matrix}\left\{\begin{matrix} 0.0078\\ 0.1286\\ 0.0555\\ 0.5021\\ 0.2019\\ 0.0145\\ 0.1471 \end{matrix}\right\}$ H_2 $\begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5 \end{matrix}\left\{\begin{matrix} 0.1839\\ 0.0002\\ 0.1590\\ 0.2443\\ 0.2480 \end{matrix}\right\}$ $H_3 \begin{matrix} s_1\\ s_2\\ s_3 \end{matrix}\left\{\begin{matrix} 0.0370\\ 0.3019\\ 0.1754 \end{matrix}\right\}$	Based on random integer number r the snails are assigned to homes $H_1 \begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5 \end{matrix}\left\{\begin{matrix} 0.0145\\ 0.1471\\ 0.2480\\ 0.3019\\ 0.1754 \end{matrix}\right\}$ H_2 $\begin{matrix} s_1\\ s_2\\ s_3 \end{matrix}\left\{\begin{matrix} 0.0002\\ 0.1590\\ 0.0370 \end{matrix}\right\}$ $H_3 \begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5\\ s_6\\ s_7 \end{matrix}\left\{\begin{matrix} 0.0078\\ 0.1286\\ 0.0555\\ 0.5021\\ 0.2019\\ 0.1839\\ 0.2443 \end{matrix}\right\}$	Best Snail Solution $H_1 0.0145$ $H_2 0.0002$ $H_3 0.0078$	New location of homes $\begin{array}{c} \\ X_1 \\ X_2 \end{array}\begin{array}{c} \begin{matrix} H_1 & H_2 & H_3 \end{matrix} \\ \begin{bmatrix} -0.0440 & 0.0037 & -0.0214 \\ -0.1122 & -0.0147 & 0.0856 \end{bmatrix} \end{array}$
⋮	⋮	⋮	⋮	⋮	⋮
Iteration 20 Equation 3 $\begin{matrix} X_1 \\ X_2 \end{matrix}\left\{\begin{matrix} [-0.9785, 0.9815] & [-0.9349, 1.0251] & [-1.0366, 0.9234] \\ [-0.9717, 0.9883] & [-0.9066, 1.0534] & [-1.0474, 0.9126] \end{matrix}\right\}$	…	Equation 10 $H_1 \begin{matrix} s_1\\ s_2 \end{matrix}\left\{\begin{matrix} 0.0107\\ 0.0036 \end{matrix}\right\}$ H_2 $\begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5\\ s_6\\ s_7\\ s_8\\ s_9 \end{matrix}\left\{\begin{matrix} 0.0036\\ 0.0252\\ 0.0012\\ 0.0007\\ 0.0862\\ 0.0031\\ 0.0023\\ 0.0053\\ 0.0051 \end{matrix}\right\}$ $H_3 \begin{matrix} s_1\\ s_2\\ s_3\\ s_4 \end{matrix}\left\{\begin{matrix} 0.0082\\ 0.0000\\ 0.0062\\ 0.0006 \end{matrix}\right\}$	Based on random integer number r the snails are assigned to homes $H_1 \begin{matrix} s_1\\ s_2\\ s_3\\ s_4 \end{matrix}\left\{\begin{matrix} 0.0012\\ 0.0023\\ 0.0082\\ 0.0006 \end{matrix}\right\}$ $H_2 \begin{matrix} s_1\\ s_2\\ s_3 \end{matrix}\left\{\begin{matrix} 0.0036\\ 0.0053\\ 0.0051 \end{matrix}\right\}$ $H_3 \begin{matrix} s_1\\ s_2\\ s_3\\ s_4\\ s_5\\ s_6\\ s_7\\ s_8 \end{matrix}\left\{\begin{matrix} 0.0107\\ 0.0036\\ 0.0252\\ 0.0007\\ 0.0862\\ 0.0031\\ 0.0000\\ 0.0062 \end{matrix}\right\}$	Best Snail Solution $H_1 0.0006$ $H_2 0.0036$ $H_3 0.0000$	New location of homes $H_1 \quad H_2 \quad H_3$ $\begin{array}{c} \\ X_1 \\ X_2 \end{array}\begin{array}{c} \begin{matrix} H_1 & H_2 & H_3 \end{matrix} \\ \begin{bmatrix} 0.0196 & -0.0705 & -0.0000 \\ -0.0134 & 0.0126 & -0.0050 \end{bmatrix} \end{array}$ $\begin{matrix} 0.0196 & -0.0134 \\ -0.0705 & 0.0126 \\ -0.0000 & -0.0050 \end{matrix}$

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Data availability The program code, results and any other related data will be made available on request.

Declarations

Conflict of interest Authors have no competing and conflicting interests of any kind.

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