Study of real-world optimization problems using advanced Nature Inspired Algorithms (NIA) discovered from 2019 to 2022

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Study of real-world optimization problems using advanced Nature Inspired Algorithms (NIA) discovered from 2019 to 2022.

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Abstract

The nature inspired algorithm (NIA) is a very essential research area that continuously facilitates finding the solution of optimization problems. NIA is one of the metaheuristic algorithm categorizations that have attracted researchers from last few decades. NIA contributes notably by dealing with many large-scale problems and attaining optimal outcomes. In this study, NIA discovered from 2019 to 2022 is listed with a brief description. The major objective of this paper is to find some best NIA for finding reasonably better solution of real-world complex optimization problems. Bearing this in mind, we have found eight common engineering problems and analyzed their solution using different NIA algorithms. Our comparative study with bibliographic analysis suggests that there are four algorithms which give us the best result for all mentioned eight engineering problems and gives us an optimal solution. This paper also gives the recent development in NIA and their application in different fields like health care, environment, industrial, commercial, machine learning and smart cities. This will support the new and developing researcher to give a broader view on NIA along with future investigation guidelines.

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1 Introduction

Optimization is an important device in making decisions and in analyzing the physical system. The main goal of optimization is to discover the optimum solution from all feasible solutions. This can be done by converting the real-life problem into a mathematical model. This mathematical modal contains objective function and a set of constraints. An objective function can be maximization or a minimization type depending on the problems. The variables are the unknowns for which we want to find values and the constraints are the relationship among the variables. There are different types of optimization problems named as continuous v/s discrete optimization, unconstrained v/s constraint optimization, single and multi-objective optimization, deterministic v/s stochastic optimization**.** Optimization problems which contain continuous variables are called continuous optimization problems and if optimization problems contain discrete variables, then it is called discrete optimization problems. A problem in which no constraints are given is called unconstrained optimization problem otherwise it is called constraint optimization problem. Optimization problems which contain one objective are called single objective problems and more than one objective is called many objective problems. Deterministic for which data are accurately known are called deterministic optimization and the use of randomness in the objective function or in the optimization algorithm refer the stochastic optimization. Along with this, there are different types of optimization methods which are classified in Figure 1. Figure 1 gives us details of all types of optimization methods used to solve every type of optimization problem (Janga and Nagesh 2020). Combinatorial optimization considers an optimal object selected from a finite set of objects, where the feasible solution set is discrete or can be brought down to a discrete set. Combinatorial optimization techniques are separated into two categories named as exact and approximate methods. A method which gives optimal solution with precision is called exact method and a method gives near optimal solution is called approximate method. Dynamic programming method and branch and bound method is exact method. Similarly continuous optimization problem is divided into linear and nonlinear programming methods. Linear- programming methods is applied when objective function and set of constraints is linear and if one of them is nonlinear then these types of problems is solved by non-linear programming methods. Simplex method and interior point search method are applied on linear programming problems. But these traditional algorithms may fail to find feasible solution on large nonlinear model (Reddy and Kumar 2012). A non-linear and approximate method is categorized in global search method and local search method. To discover the optimal solution from the specific region of the search space is called local search and to discover the optimal solution from the whole search space is called global search. On the other hand, we can say that local optima lie in global optima. Global search method is classified into three parts, viz. Heuristic, Metaheuristic and random search. Heuristic algorithm is a population-based algorithms and it is inspired by the biological or human intelligence phenomenon. These algorithms show optimal solution or near optimal solution. Heuristic algorithms are strongly problem dependent. In random search (RS) methods, functions may or may not be continuous and differentiable. Such optimization methods are also known as derivative-free methods. Local search technique is divided into gradient-based optimization and non-gradient-based optimization. Gradient based optimization presents a powerful method if the objective function of an optimization problem is differentiable and gradient information is consistent. If the objective function is differentiable but finding the derivative is difficult then derivative free methods are extremely useful optimization tools. Recently nature inspired metaheuristic algorithms gained more attention of researcher to solve complex problems. The metaheuristic is the combination of two Greek terminology "meta" and "heuristic". The heuristic expresses' 'to discover', and the meta expresses ''away from, in an better level'' (Muazu et al. 2022). Meta heuristics is appropriately defined as a repetitive generation procedure that is conducted by

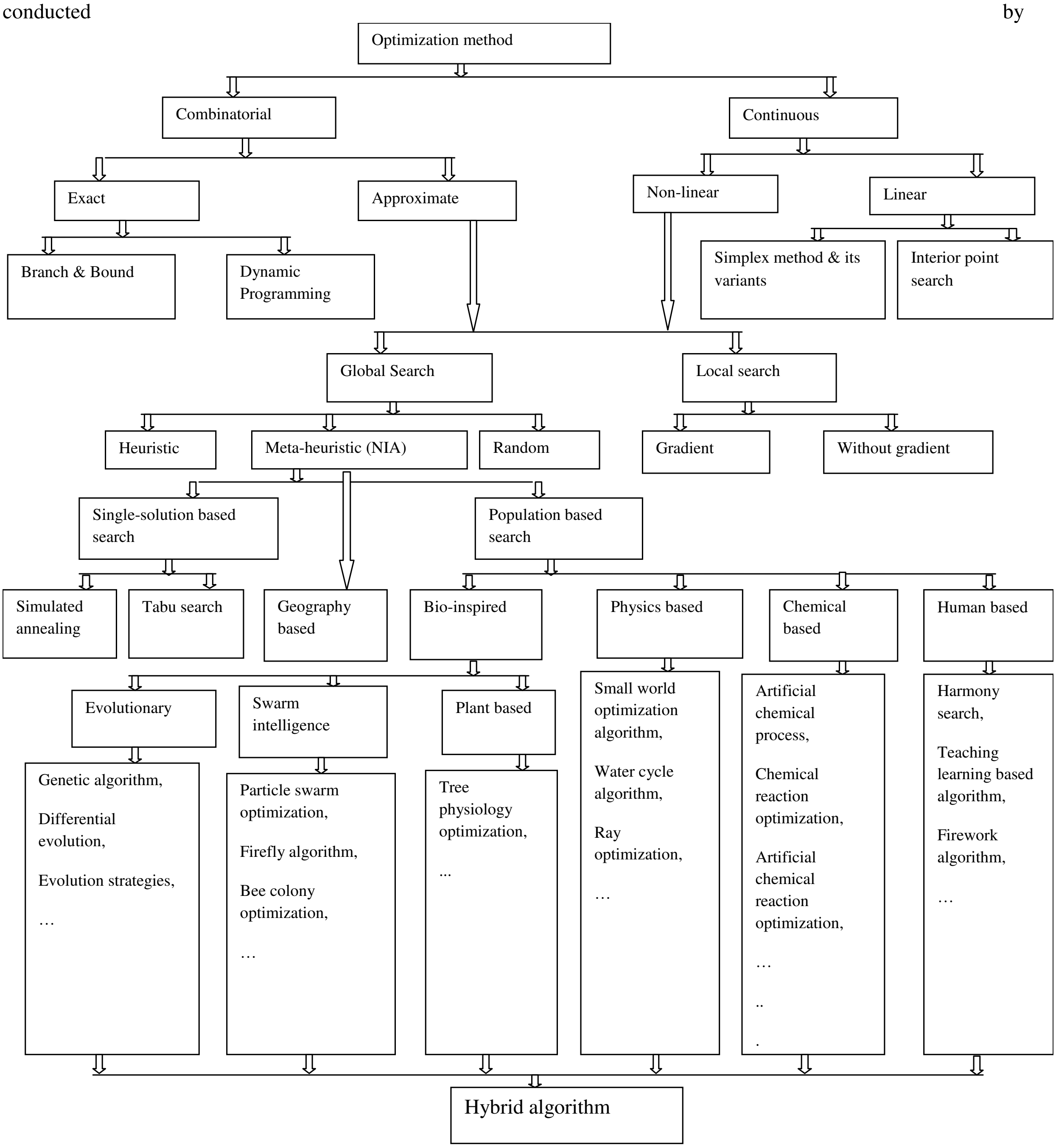

Fig. 1 Classification of optimization methods.

Collaborate dissimilar intelligent approaches to investigate the exploration space, learning policies used to composition information to get proficiently close to the optimal solutions. All metaheuristics are NIA depending on numerous bases from physical, biology and ethology (Suman and Kumar 2006). These techniques are usually divided into two classes namely population-based metaheuristic and single solution-based algorithm. Single solution-based NIA utilizes solo candidate solutions and develops his results with local search. But the result acquired from single solution may be trapped in local optima. The famous single solution dependent metaheuristics are Tabu search and Simulated Annealing. Population based search methods are divided into bio-inspired, physical based, chemical based, and human based. Bio-inspired is further divided into evolutionary algorithm, swarm intelligence algorithm and plant based algorithm. These algorithms can be hybridized together to advance the superiority of the solution.

2 A cyclopedia of NIA

This section aims to provide summarizing information about the earlier surveys on NIA discovered between 2019 to 2022.The list of the NIA discovered in this period is reported in Table 1. Along with algorithm and author name few remarks are also given in table 1 which gives the source of inspiration of all newly developed algorithms. Each algorithm has initially worked on some benchmark problems for validation then thereafter few engineering problems have been solved using these algorithms. In the last column, we also have mentioned a list of those engineering problems.

Table 1 List of NIA discovered from 2019-2022

S.No.	Name of the algorithm	Author Name	Remarks	Problems
1	Harris Hawks Optimization (HHO)	Heidari et al. 2019	HHO is motivated by the chasing style and cooperative activities by the hawks.	Three-bar truss, Tension/compression spring design, Pressure vessel design, Welded beam design, Multi-plate disc clutch brake, Rolling element bearing, Benchmark functions
2	Sailfish Optimizer (SFO)	Shadravan et al. 2019	SFO is encouraged by the hunting selfish group. SFO contains two type of population, selfish population to increase the best search and modify the search space of the population of crowd. SFO technique outperform for non-separable, non-convex and scalable test functions.	I-beam design, Welded beam design, Gear train design, Three-bar truss design, Circular antenna array design, Benchmark functions
3	Pathfinder Algorithm (PFA)	Yapici and Cetinkaya 2019	PFA is stimulated by the cooperative behavior of animals in exploration of food. PFA was discovered to solve multi objective problems. PFA display very combative result related to famous NIA such as particle swarm optimization.	Tension/compression spring design, welded beam design, pressure vessel design and cantilever beam design, Benchmark functions.
4	Seagull Optimization Algorithm(SOA)	Dhiman and Kumar 2019	SOA is motivated by repositioning and aggressive behavior of seagull in nature. The behavior of seagull is modeled mathematically and applied to highlight exploitation and exploration in a specified search space. Investigational results find that SOA method is useful to solve extensive optimization difficulty and is extremely competitive to other famous NIA.	Constraint handling, Optical buffer design, Pressure vessel design, Speed reducer design, Welded beam design, Tension/compression spring design, 25-bar truss design, Rolling element bearing design, Benchmark functions
5	Optimization Booster Algorithm (OBA)	Pakzad-Moghaddam et al. 2019	OBA is enthused by human intelligence along with to boost the business in exchange market. The main objective in replace market is to raise the profit ultimately.	Pressure vessel design, welded beam design, bi-objective centrifugal pump design, travelling salesman problem, Benchmark functions
6	Henry Gas Solubility Optimization (HGSO)	Hashim et al. 2019	HGSO algorithm is stimulated by the assemble actions of gas to steadiness investigation and management in the explore space to stay away from local optima. The experimental results revealed that HGSO is useful to solve large scale optimization problems.	Welded beam design, Tension/compression spring design, Speed reducer design, Benchmark functions
7	Sea Lion Optimization (SLnO)	Masadeh et al. 2019	The SLnO method is inspired by the confine activities of sea lions in environment. Furthermore, it is motivated from sea lions' stubble to get the quarry.	Benchmark functions
8	Naked Mole-Rat	Salgotra and Singh	This NMR algorithm is encouraged by the	Benchmark functions

	(NMR) Algorithm	2019	copulating process of NMRs in natural world. Two categories of NMRs are used to characterize these patterns called breeders and worker. Workers continuously struggle to convert into breeders, whereas breeders become competitors to intimate with the queen. Breeders who are infertile are not counted and the suitable worker converted into a new breeder. This knowledge has been utilized to build up the NMR technique.	
9	Nuclear Reaction Optimization (NRO)	Wei et. al. 2019	NRO is enthused by the NR procedure and contain of two steps, namely, a nuclear fusion (NFu) step and a nuclear fission (NFi) step.	welded beam design, pressure vessel design and tension/compression spring design, Benchmark functions
10	Atom Search Optimization(ASO)	Zhao et al. 2019	ASO is stimulated by fundamental molecular dynamics. It is urbanized to identify a dissimilar location of optimization difficulty. Mathematical models of ASO stimulate the movement of atomic model in nature. ASO is simple and effortlessly applied.	Hydro geologic parameter estimation, Benchmark functions
11	Search and Rescue (SAR)Optimization	Shabani et. al. 2019	SAR was discovered for solving one objective continuous problems of optimization. SAR is stirred by the explorations accepted out by humans during investigation and rescue operations.	I-Beam Design, Cantilever Beam Design, Spatial 25-Bar Truss Structure Design, Benchmark functions
12	Wildebeest Herd Optimization (WHO)	Amali and Dinakaran 2019	WHO is encouraged by the herding behavior of Wildebeest. WHO algorithm outperforms on large search range problems and high dimensional problems.	Benchmark functions
13	Butterfly Optimization Algorithm(BOA)	Arora and Singh 2019	BOA is motivated by the mating and butterflies behavior for food search, to solve large scale problems of optimization. The structure is motivated by the foraging approach of butterflies, which consume their intelligence of smell to identify the position of mating or nectar co-worker.	Spring design, welded beam, and gear train design, Benchmark functions
14	Blue Monkey Algorithm (BMA)	Mahmood and Al-Khateeb 2019	BMA is encouraged by the presentation of blue monkey crowd in nature. The BM algorithm identifies the no. of males in one group. Normally, exterior the season of the reproduction, the groups of blue monkeys have only one mature male like other forest guenons. This algorithm is well-organized in field of dissolving real problems with boundaries and mysterious search space.	Benchmark functions
15	Emperor Penguins Colony (EPC) Optimizer	Harif et. al. 2019	EPC method is encouraged from the performance of emperor penguins. This algorithm is proscribed by the heat of the body waves of the penguins and curved-like faction of them in their settlement	Benchmark functions
16	Future Search Algorithm (FSA)	Elsisi 2019	FSA is inspired by the person's life. Inhabitants in the world investigate for the best life. If some person initiates that his life is not good quality, he tries to modify it and he imitates the victorious persons. This algorithm is converted into mathematical equations according to this behavior.	Benchmark functions
17	Chimp Optimization Algorithm(ChOA)	Khishe and Mosavi 2020	Entity cleverness and sensual stimulus of chimps in their crowd hunting is the main inspiration of ChOA, which is not same from the additional common animal of prey. ChOA is premeditated to more improve the two difficulty of measured speed of convergence and pin down during local optima for high-dimensional optimization problems.	Heat Exchanger Network Design , Reactor Network Design, Two-reactor Problem ,Multi-product batch , Optimal Design of Industrial refrigeration

				System,Optimal Sizing of Distributed Generation for Active Power Loss, Minimization, Optimal Power flow (Minimization of Active Power Loss), SOPWM for 3-level Inverters,Beef Cattle, Benchmark functions
18	Slime MouldAlgorithm(SMA)	Li et al. 2020	SMA is motivated from the fluctuation style by the slime mould in natural world. SMA have numerous fresh features among a exceptional mathematical representation that utilize acceptable weights to imitate the procedure of built negative and positive advice of the transmission signal of slime mould depend on bio-vibrator to the most favorable pathway for involving food with brilliant investigative capability and exploitation tendency.	Welded beam, pressure vessel, cantilever, and I-beam design, Benchmark functions
19	Gradient-based Optimizer (GBO)	Ahmadianfar et al. 2020	GBO is encouraged by the Newton's method based on the gradient, utilize two major machinist: gradient search rule (GSR) and local escaping operator (LEO) and vectors set to travel around the investigate space. GSR engage the gradient-based technique to improve the investigation and speed up the rate of convergence to attain improved positions in the investigate space.	Speed reducer, Three-bar truss, I-beam design, Cantilever beam, Rolling element bearing design, Tension/compression spring design, Benchmark functions
20	Marine Predators Algorithm (MPA)	Faramarzi et al. 2020	MPA is motivated by the common foraging approach specifically enlist and tectonic activities in marine predators alongside with optimal bump into rate approach in biological contact between marauder and prey. MPA mimics the policy that unsurprisingly run in best foraging policy and experience rate strategy among marauder and prey in marine atmosphere.	Pressure vessel design, welded beam design, and tension/compression spring design, Benchmark functions
21	Mayfly Optimization Algorithm (MOA)	Zervoudakis and Tsafarakis 2020	MOA mimic the voyage activities and the mating course of action of mayflies. MOA is the mixture of most imperative benefit by swarm intelligence and evolutionary algorithm. The procedure of connubial dance as well as arbitrary gliding improves the stability in the middle of algorithm's exploitation and exploration effects and averts it coming out of local optima.	flow-shop scheduling problem, Benchmark functions
22	Manta Ray Foraging Optimization (MRFO)	Zhao et al. 2020	Intellectual behavior of manta rays is the main inspiration of MRFO. MRFO used three distinct foraging policies of manta rays, together with, cyclone foraging, somersault foraging and chain foraging, to advance an well-organize optimization representation for discover the answer of dissimilar optimization problems.	Tension/compression spring design, Pressure vessel design, Welded beam design, Speed reducer design, Rolling element bearing design, Multiple disc clutch brake design, Belleville spring design, Hydrostatic thrust bearing design, Benchmark functions
23	Billiards-inspired Optimization Algorithm (BOA)	Kaveh et al. 2020	BOA method inspired by the billiards game. Every candidate is identified like a billiards ball of multi-dimensional and the most excellent solution is known as a patch. While the balls come across another balls, conservation laws and vector algebra make a decision about the last locations of the balls in investigate space	Design of a welded beam, Design of the cylindrical pressure vessel, Design of a tension/compression spring, Design of a cantilever beam, Design of the special 72-bar truss, Design

				of the 120-bar dome-shaped truss structure, Design of the planar 200-bar truss structure, Benchmark functions
24	Equilibrium Optimizer (EO)	Faramarzi et al. 2020	EO is stimulated by manage mass volume balance models utilized to estimation both equilibrium and dynamic state. Each candidate performs as a search mediator in EO. The candidates randomly update their reflection in respect of best candidate to achieve the optimal state which is identified as equilibrium candidates EO has an ability in investigation, management, and avoidance of local optima in search space.	Pressure vessel design, Welded beam design, Tension/compression spring design, Benchmark functions
25	Coronavirus Optimization Algorithm (COA)	Martínez-Álvarez et al. 2020	COA mimics the strategy of corona virus increment and infection of the healthy people. The COA has two most important benefits as compared to other algorithm. The input parameter is previously set so there is no requirement to initializing it with random value. Second, COA has the capability to finish after numerous iterations, beyond locale this value also.	
26	Sparrow Search Algorithm(SSA)	Xue and Shen 2020	SSA is motivated from the group intelligence, foraging and conservation activities of sparrows.	Himmelblau's nonlinear optimization problem, Speed reducer design, Benchmark functions
27	Sandpiper Optimization Algorithm(SOA)	Kaur, Jain and Goel 2020	SOA is encouraged from the resettlement and striking activities by the sandpipers. The two footstep resettlement and striking activities are customized and computationally executed to highlight diversification and intensification inside the exploration space.	Constraint handling, Optical buffer design, Pressure vessel design, Speed reducer design, Welded beam design, Tension/compression spring design, 25-bar truss design, Rolling element bearing design, Benchmark functions
28	Black Widow Optimization (BWO) Algorithm	Hayyolalam and Kazem 2020	BWO is enthused from the distinctive coupling performance by the black widow spiders. BWO technique involved a restricted step which is named as cannibalism. Species through unsuitable fitness are lost from the ring due to this step, thus premature convergence is obtained. BWO is helpful to solve non linear and continuous optimization problems.	pressure vessel designs, welded beam, and tension/compression spring, Benchmark functions
29	Forensic-Based Investigation (FBI) Optimization	Chou and Nguyen 2020	FBI is motivated from the guess inquiry spot recognition procedure that is worn by police force. Although several awkward optimization algorithms hang up their serviceability by requiring calculated operating parameters. FBI is an easily operated algorithm that requires unarranged operating parameters.	Resource-constrained project scheduling problem, benchmark functions
30	Bald Eagle Search (BES)	Alsattar et al. 2020	BES is influenced from the hunting approach or sharp collective actions by the bald eagles like they investigate for prey. Hunting behavior of BES is separated in three steps. First steps is called "selecting space" in which an eagle select the space with a large amount of prey. Second step is called "searching in space" in which the eagle goes inside the chosen space to look for prey. And the third step is called "swooping" in which the eagle oscillates from the best position recognized in the second step and decide the best location to	Benchmark functions

			hunt.	
31	Life Choice-Based Optimization(LCBO)	Khatri et al. 2020	LCBO mimics the distinctive judgment-making capability of human being to reach their target while erudition from associate members. LCBO is a future optimization technique for solving engineering problems.	Pressure vessel design, Cantilever beam design, Benchmark functions
32	Social Ski-Driver (SSD) Optimization	Tharwat and Gabel 2020	This algorithm is motivated from distinct evolutionary algorithms which are applied to enhance the framework of support vector machines (SVMs), to improve the categorization performance.	Eight standard imbalanced datasets were used for testing the proposed algorithm
33	Artificial Ecosystem-based Optimization (AEO)	Zhao et al. 2020	AEO is an inhabitants-based optimization technique stimulated by the energy flow in an environment and AEO is inspired by the three distinctive behaviors of critter as well as construction, utilization, and decomposition.	welded beam design, three-bar truss design, tension/compression spring design, cantilever beam design, pressure vessel design, speed reducer design, rolling element bearing design, and multiple disk clutch brake design, Benchmark functions
34	Heap-based Optimizer (HBO)	Askari et al. 2020	HBO is encouraged by a set of inhabitants running for a frequent aim but may not complete their aim except they assemble themselves within a sequence called commercial Rank Hierarchy (CRH). HBO search agents are layout in a chain according to their fitness value. Heap data structure is utilized in HBO to plot the concept of CRH. This algorithm is named heap-based optimizer (HBO).The numerical form of HBO is depends on the three extremity: the associations among the subordinates as well as their instant superior, the communication involving the age group, and employees self-involvement.	Speed reducer design, multiple disc clutch brake design, and rolling element bearing design, Benchmark functions
35	Color Harmony Algorithm (CHA)	Zaeimi and Ghoddosian 2020	CHA is proposed for finding the solution for global optimization problems. CHA represents it's investigation performance between integrating colors of harmonic depending upon their comparative positions in the region of the shade disk in the munsell shade arrangement and harmonic device. CHA has two non-identical stages together with the attention and the distribution stage which are engaged to discover and develop the investigation space.	Benchmark functions
36	Stochastic Paint Optimizer (SPO)	Kaveh et al. 2020	SPO is a inhabitants-based optimization technique which is motivated by the painting art and the colors beauty.	52-bar planar truss structure, 120-bar dome truss structure, 3-bay 15-story frame, A 3-bay 24-story frame, Benchmark functions
37	Political Optimizer(PO)	Askari et al. 2020	PO is moved by the multi-step course of politics. In PO, population is partitioned into electorate and political parties, in which every candidate is ease to renovate its position according to the party leader and the public winner. PO is uniform to function changing and act constantly for multi dimensional investigation spaces.	Welded beam design, speed reducer design, pressure vessel design and tension/compression spring design, Benchmark functions
38	Water Strider Algorithm (WSA)	Kaveh et al. 2020	WSA is motivated by the self-protective behavior, intelligent flow conveying, feeding, coupling style apparatus, and progression of water voyager insects.	Welded beam design, Three-bar truss design, Compound gear design, Cantilever beam design, Benchmark

				functions
39	Newton Metaheuristic Algorithm (NMA)	Gholizadeh et al. 2020	NMA was discovered to solve isolated act based tectonic design of steel substance stands. The Newton method, as its updating method is utilized in NMA for population-based structure. So, it is named NMA.	52-bar truss, 200-bar truss, 3 performance-based design optimization examples
40	Giza Pyramids Construction based Optimizer (GPC)	Harif et al. 2021	GPC is motivated by the past of the ancient. GPC has the distinctiveness of a good quality metaheuristic technique to contract through various issues. The ancient, motivated approach is to examine and imitate the inheritance of the antique past to recognize the optimal techniques, mechanics, and plan of action of that stage. GPC is proscribed by the actions of the employees approaching the rock bar on the access ramp. GPC is useful for find the solution of multi dimensional problems, mostly image segmentation problem.	Benchmark functions
41	Gaining Sharing Knowledge-based (GSK) Algorithm	Mohamed et al. 2020	GSK is useful for continuous optimization difficulty. GSK technique mimics the procedure of sharing and gaining information throughout the individual life period. It is constructed on two imperative steps, senior sharing and gaining step and junior sharing and gaining step. GSK is capable of solving high dimensional optimization problem.	Benchmark functions
42	African Vulture's Optimization Algorithm (AVOA)	Abdollahzadeh et al. 2021	AVOA is encouraged by African vultures' way of life. AVOA simulates African vultures' foraging and map-reading behaviors.	The three-bar truss design problem, The welded beam design, Multi-plate disc clutch brake, Pressure vessel design, Tension/compression spring design, Rolling element bearing design, Spacecraft trajectory optimization problem, Lennard-Jones potential problem, Static economic load dispatch problem, IIR digital filtering systems modeling problem, Benchmark functions
43	Remora Optimization Algorithm (ROA)	Jia et al. 2021	The idea for ROA is primarily due to the bloodsucking behavior of remora. ROA is more trending to give a new proposal for memetic algorithm.	I-beam design, Welded beam design, Pressure vessel design, Three-bar truss design, Rolling element bearing, Benchmark functions
44	Chameleon Swarm Algorithm (CSA)	Braik 2021	CSA is revealed for global mathematical optimization difficulty. CSA is motivated by the activities of chameleons when hunting and navigating for ration origin on plants, leave and close to morass. CSA is modeled mathematically and apply the chameleons behavior step in investigation for rations, together with their performance in revolving his eyes to a virtually 360° range of visualization to situate quarry and capture quarry using their steamy tongues that instigate at lofty swiftness. These foraging device strained	welded beam design, the pressure vessel design, the tension/ compression spring design, the speed reducer design and the rolling element bearing design, Benchmark functions

			from chameleons ultimately guide to possible solutions when appealed to deal with optimization difficulty.	
45	Artifcial Gorilla Troops Optimizer (GTO)	Abdollahzadeh et al. 2021	GTO is motivated by gorilla troops' communal cleverness in natural world. In GTO gorillas' cooperative behavior is mathematically drawn and novel device are intended to act exploitation and exploration.	Parameter estimation for Frequency-Modulated sound waves, Circular antenna array design problem, Spread spectrum radar polyphase code design problem, Cassini Spacecraft trajectory optimization problem, Messenger: spacecraft trajectory optimization problem, Lennard–Jones potential problem, Static economic load dispatch problem, Benchmark functions
46	Coronavirus herd immunity optimizer (CHIO)	Al-Betar et al. 2021	CHIO mimic the herd immunity conception to deal with corona virus pandemic (COVID-19). The spreading speed of corona virus infection depends on the infected persons directly get in touch with other society persons. To prevent other members of the public from this infection, social distancing is recommended by health experts. CHIO is motivated by herd immunity approach in addition to the social idea.	Parameter estimation for frequency-modulated sound waves, bifunctional catalyst blend optimal control problem, Transmission network expansion planning (TNEP) problem, Benchmark functions
47	Flow Direction Algorithm (FDA)	Karami et. al. 2021	FDA technique is based on physics. FDA technique is inspired by the flow pathway to the opening spot with the buck tallness in a sewerage sink.	Three-bar truss, tension/compression spring, speed reducer, gear train, and welded beam design, Benchmark functions
48	Aquila Optimizer (AO)	Abualigah et. al. 2021	AO method is stimulated by the behaviors of Aquila’s in environment during contagious the prey. AO method are constitute in four steps; pick the investigate space by elevated ascend through the vertical bend, traverse inside a separate investigate space by curve flight with little slide hit, utilize inside a range investigate space by small trip with sluggish fall assault, and drop by stroll and grasp quarry.	Tension/compression spring design, pressure vessel design, welded beam design, 3-bar truss design, speed reducer, cantilever beam design, and multiple disc clutch brake, Benchmark functions
49	QANA: Quantum-based Avian Navigation Optimizer	Zamani et al. 2021	QANA is a novel differential evolution (DE) algorithm stimulated by the amazing correctness routing of wandering birds throughout extensive distance in flight pathways.	Tension/compression spring, Pressure vessel design, Three bar truss, Welded beam, Benchmark functions
50	Atomic Orbital Search (AOS)	Azizi 2021	AOS is inspired by the philosophy of quantum technicalities and the atomic model based on quantum to which the common arrangement of electrons about nucleus is within perception. AOS algorithm is capable to handling with the engineering and mathematical problems.	Speed reducer, Pressure vessel, Welded beam, Tension or compression spring, Multiple disk clutch brake, Benchmark functions
51	Arithmetic Optimization Algorithm (AOA)	Abualigah et. al. 2021	AOA is aggravated by the activities of the arithmetic operators of mathematics.	Welded beam design, tension/compression spring design, pressure vessel design, 3-bar truss design, and speed

				reducer , Benchmark functions
52	Dingo Optimizer (DOX)	Bairwa et al. 2021	DOX mimic the social activities of dingoes. DOX is inspired from the trapping actions by the dingoes that contain investigation, encompassing, and management.	Pressure Vessel Design, Benchmark functions
53	Red Colobuses Monkey (RCM)	Al-Kubaisy et al. 2021	RCM is annoyed by the actions of red monkey in nature.	Benchmark functions
54	Archimedes Optimization Algorithm (AOA)	Hashim et. al. 2021	AOA is inspired from an Archimedes' Principle of physics. It emulates the rule of buoyant force employ upon a thing, incompletely or entirely absorbed within fluid, is relative to heaviness of the replaced fluid. AOA is a good optimization device with respect in the direction of speed of convergence and investigation-management stability, as it is successfully relevant for solving complex optimization difficulty.	Welded beam design, Tension/compression spring design, Speed reducer design, : Pressure vessel design, Benchmark functions
55	Rat Swarm Optimizer (RSO)	Dhiman et.al. 2021	The main encouragement of RSO is the hunting and aggressive activities of rats in natural world. RSO is very successful for finding the solution of real life optimization difficulty.	Pressure vessel, speed reducer, welded beam, tension/ co-mpression spring, Rolling element bearing design problem, 25-bar truss design, Benchmark functions
56	Hunger Games Search (HGS)	Yang et al. 2021	HGS is aggravated by appetite activities and behavioral preference of animals. It acts in according with computationally analytical rules used by approximately the entire animals and their competitor actions and sports event are frequently acceptable by connect advanced probability of existence and food achievement. HGS is a method of energetic nature, easy composition and good performance in conditions of convergence and satisfactory value of answers, showing to be extra resourceful than the present optimization techniques.	Welded beam design, I-beam design, Multiple disk clutch brake, Benchmark functions
57	Horse Herd Optimization Algorithm (HOA)	Miar et al. 2021	HOA is stimulated by horses' herding activities for multi dimensional optimization difficulty. HOA copy the social recital from horses at unlike generation using six important qualities: ruminate, hierarchy, affability, imitation, resistance device and roam. HOA has a good optimization tool for solving high dimensional complex problems.	Benchmark functions
58	Preaching-inspired Optimization Algorithm (POA)	Wei et. al. 2021	POA is encouraged by the "preachers" social activities. Convergence accuracy of POA becomes better quality by developing the primary choice of offspring persons. By instigate the collective weight together with individuals strength and location connection between persons, the assortment of persons is enhanced, thus tumbling the likelihood of POA early convergence	Pressure vessel design, Welded beam design, Tension/compression spring design, Benchmark functions
59	Battle Royale Optimization Algorithm (BRO)	Rahkar 2021	BRO is stimulated by a nature of cybernetic games named as "battle royals." BRO is introduced as an inhabitants-based optimization method in which each entity is represented through a performer that would be similar tomove in the direction of the best position and eventually continue to exist.	BRO for inverse kinematics of robot arms, Benchmark functions
60	Cat and Mouse Based Optimizer (CMBO)	Dehghani et al. 2021	CMBO is aggravated by the ordinary activities between mice and cat. In CMBO, the faction of cats with regard to mice in addition to the run-away of mice	Benchmark functions

			with regard to paradise is imitated.	
61	Tuna Swarm Optimization (TSO)	Xie et. al. 2021	TSO is inspired from the supportive foraging actions by tuna swarm. The exertion imitates two grazing deportment by tuna swarm, as well as parabolic grazing and spiral grazing, for rising an efficient metaheuristic techniques.	Pressure vessel design, the tension/compression spring design, and the welded beam design, Benchmark functions
62	Past Present Future (PPF): a new Human-based Algorithm	Naik and Satapathy 2021	PPF is stimulated the experience of the organization gain from a victorious person in the world. PPF is motivated by the idea of future development of a human life turns on their precedent knowledge and at hand effort. The power of victorious humans also influenced by the development of the prospect existence of an human being.	Tension/compression spring design, welded beam, Gear train design , Cantilever beam design, Three-bar truss design, Benchmark functions
63	Aptenodytes Forsteri Optimization (AFO) Algorithm	Yang et. al. 2021	Emperor penguin's temperate hugging activities are the main motivation of AFO. When finding an appropriate position, emperor penguins require to awareness the interchange in temperature and consider the position of additional penguins, go near to the nucleus of penguin inhabitants, reduce their power loss, and mention to their remembrance. These plans of action are developed into five bring up to date way of variables. Adaptive adjustments techniques are planned to merge the five behaviors according to the uniqueness of these update modes in the exploration and exploitation phase.	Three bar truss design, Welded beam structure, Tension/compression spring design and Cantilever structure problem, Benchmark functions
64	Learner performance-based behavior (LPB) algorithm	Rahman and Rashid 2021	LPB stimulate the method of tolerant graduated student of high school in different departments in university. Additionally, the changes in the students should execute within their studying performance to get better their reading period in university. The popular main steps of optimization; exploration and exploitation are lineaments by conniving the procedure of long-suffering graduated beginner by high school to institution of higher education and the process of humanizing the beginner's learning performance in university to develop the intensity of their education.	Benchmark functions and aassignment problem
65	Material generation algorithm (MGA)	Talatahari et al. 2021	Some higher and necessary feature of data science, particularly the arrangement of chemical mixtures as well as chemical response in fabricate new resources, are set on as encouraging hypothesis of the MGA.	Speed Reducer, Tension/Compression Spring,PressureVessel,WeldedBeam,Three-Bar Truss,Multiple Disk Clutch Brake, Planetary Gear Train, Step-Cone Pulley, , Hydrostatic Thrust Bearing, Ten-Bar Truss, Rolling Element Bearing, Gear Train, Steel I-Shaped Beam, Piston Lever, Cantilever Beam, Benchmark functions
66	Child Drawing Development Optimization (CDDO)	Abdulhameed and Rashid 2022	CDDO technique stimulated by the knowledge actions of the child's as well as cognitive improvement by the fair proportion to upgrade the prettiness beyond their skill. CDDO utilize golden ratio and imitate logical education and child's sketch progress periods opening from the scrawling phase to the higher design-based phase	Benchmark functions
67	Bonobo Optimizer	Das and Pratihar 2022	BO is motivated by the different	Tension/compression

	(BO)		interesting generative plans and social activities by the Bonobos. Bonobos survive in a cleaving-blending style of community association, where they figure numerous groups of dissimilar sizes and conformation inside the culture and progress during the province. Later they combine once more through their civilization members intended for managing distinct behavior. Bonobos accept four unlike generative plans, like preventive coupling, immoral coupling, additional-group coupling and partnership coupling to continue a suitable agreement in the the world.	spring, pressure vessel, welded beam and speed reducer gear system designs, Benchmark functions
68	Reptile Search Algorithm (RSA)	Abualigah et. al. 2022	RSA is aggravated from the hunting actions by crocodiles. Two main stages of crocodile activities are executed, like encompassing that is executed by high strolling or stomach strolling, and trapping that is executed by trapping management or trapping collaboration.	Pressure vessel design, welded beam design, tension/compression spring design, 3-bar truss design problem, Speed reducer problem, Cantilever beam design problem, and Multiple disc clutch brake problem, Benchmark functions
69	Driving Training-Based Optimizatio n (DTBO)	Dehghani et al. 2022	DTBO is encouraged by the human action of driving guidance. DTBO is stimulated by the education procedure of operate in the operating school and the guidance of the operating coach. DTBO is accurately customized in three stages: guidance by the operating coach, affecting of students by teacher expertise and performs.	Pressure vessel design and welded beam design, Benchmark functions
70	Pelicon optimization algorithm (POA)	Trojovský and Dehghani 2022	POA mimic the ordinary activities of pelicans throughout trapping. In POA, hunt members are pelicans that investigate for origin of the food.	Pressure vessel design, speed reducer design, welded beam design, and tension/compression spring design, Benchmark functions
71	Circulatory system based optimization (CSBO)	Ghasemi et al. 2022	CSBO is a bio-stimulated method is revealed to crack big level optimization problems. CSBO is modeled mathematically based on body's blood vessels function in the body with two distinguishing circuits, i.e. systematic and pulmonary circuits. The outcomes specify that CSBO is profitably attained the optimal answers of the problem and prevent from local optima.	Tension/compression spring, three-bar truss and pressure vessel, Benchmark functions
72	Cheetah optimizer (CO)	Akbari et al.2022	Cheetahs normally use three plans of action for trapping quarry i.e., penetrating, sitting and awaiting, and castigating. These game plans are affected in this vocation. Moreover the abscond petition and exit reverse home policy is also included in the trapping procedure to recover the projected structure population variegation, convergence presentation, and sturdiness. CO can be effectively crack big scale and demanding optimization issues and provide a major improvement over dissimilar principles and enhanced and mixture accessible methods.	Benchmark functions and aeconomic load dispatch problem in power system
73	Prairie dog optimization (PDO) algorithm	Ezugwu et al. 2022	PDO is encouraged from the performance by the prairie dogs in his ordinary habitation. PDO uses four activities of prairie dog to complete the two common optimization stages, investigation and management. Prairie dogs' grazing and burrow construct actions are used to give examining performance for PDO. Prairie	Welded beam design, pressure vessel design, compression spring design, speed reducer design, three-bar truss design, gear train design, cantilever beam

			dogs construct his burrows in the region of a generous food resource. As the food origin gets exhausted, they investigate for a fresh rations source and construct fresh burrows throughout it, surveying the entire community or complication place to determine novel ration origin or solutions.	design, optimal design of I-shaped beam, tubular column design,piston lever design problem, Benchmark functions
74	Gazelle optimization algorithm (GOA)	Agushaka et al. 2022	GOA is stimulated by the gazelles' endurance ability in their marauder conquered environment.	Welded beam design, Compression spring design, Pressure vessel design, speed reducer design, Benchmark functions
75	Mountain Gazelleoptimizer (MGO)	Abdollahzadeh et al. 2022	MGO encouraged by the collective living and grading of wild mountain gazelles. In MGO 'gazelles' pecking order and collective life is put together modeled mathematically and utilized to build up an optimization technique.	Frequency-Modulated Sound Waves Parameter Estimation, Circular Antenna Array Design Problem, Spread Spectrum Radar Polly phase Code Design problem, Cassini Problem of Spacecraft Trajectory Optimization, Messenger: A Problem of Spacecraft Trajectory Optimization, Lennard-Jones Potential Problem, Problem of Static Economic Load Dispatch (ELD), Benchmark functions
76	chef-based optimization algorithm (CBOA)	Trojovská and Dehghani 2022	CBOA is motivated by the development of cooking knowledge expertise in guidance journey. The steps of the cooking schooling course in dissimilar steps are modeled mathematically adapted with the plan of growing the capability of universal investigate in searching and the capacity of local investigation in searching.	Pressure vessel design, speed reducer design, welded beam design, structural tension/ compression springs design, Benchmark functions
77	Hunter- prey optimization (HPO)	Naruei and Sabbagh 2022	HPO is stimulated from the performance of marauder animals like lions, wolves and leopards, and quarry like gazelle and celibate. In HPO a quarry and carnivore inhabitants and a carnivore criticizes quarry that go left from the quarry inhabitants. Hunter modifies his location regarding this distant quarry, and the quarry adapts his location to a protected place. The exploration representation location that was the greatest importance of the fittingness purpose measured a protected place.	Speed reducer design, rolling element bearing, cantilever beam design, multi-plate disk clutch brake, welded beam, three-bar truss, step-cone pulley problem, pressure vessel designs and tension/compression spring, Benchmark functions
78	Sheep Flock Opti mization Algorith m (SFOA)	Kivi and Majidnezhad 2022	SFOA is stimulated by the sheep guy and sheep conduct in the grassland. SFOA include three move style (1) sheep man supervision (2) previous best knowledge of sheep's (3) move toward of sheep's to another sheep. The gather portion is recurring systematically after different repetitions of the shift portion. A sheep is a result, and grazing land is the area of the problems, rations count in every point is the strength function of the method, and goal is to increase access to major rations sources.	tension/compression spring and pressure vessel design, Benchmark functions
79	Wild horse optimizer (WHO)	Naruei and Keynia 2022	The social interactions of wild horses inspire WHO. Horses typically live in herds that include a stallion, numerous mares, and foals. Horses engage in a	Heat exchanger network design, Process synthesis and design problem,

			variety of behaviors, including grazing, ruling, pursuing, mating, and leading. Horses' civility is a charming trait that sets them apart from other animals. Horses behave well when their calves leave their group before they reach adolescence and join other herds. To stop the father from mating with the daughter or other family members, he is leaving. The proposed algorithm was primarily inspired by the horse's decent behavior.	Two-reactor problem, Process synthesis problem, Tension/compression spring design, Three-bar truss design problem, Step-cone pulley problem, Rolling element bearing, Gas transmission compressor design, Himmelblau’s function, benchmark functions

Along with developing new algorithms, few researchers also have written review papers in between 2019 to 2022 and the details of them is mentioned in Table 2

Table 2 Review papers on NIA between 2019-2022

Sr. No.	Author	Summary
1	Dokeroglu et al. 2019	In this paper the nature stimulated metaheuristic algorithms of the previous two decades is reviewed. As per their review, a metaheuristic algorithm developed before the year 2000 is called a "classical" metaheuristic algorithm. They briefly explained these classical metaheuristics along with fourteen new metaheuristic algorithms discovered between 2000 and 2020.
2	Yang 2020	The focus of this study is on the search processes and mathematical underpinnings of some recent nature-inspired algorithms. Five unresolved concerns relating to the investigation of algorithmic convergence and stability, parameter tuning, the mathematical framework, the function of benchmarking and scalability are highlighted. The first concern is to create a unified framework for mathematically analyzing all nature-inspired algorithms in order to learn in-depth details about their convergence, rate of convergence, stability, and robustness, and second concern is to best adjust an algorithm's parameters in order to get the best results for a specific set of problems and control these parameters so as to maximize the performance of an algorithm. The third concern is the use of benchmark functions to examine how the new algorithm might perform in contrast to other algorithms is a vital study for any new algorithm, especially one inspired by nature. Through this benchmarking, researchers can better understand the algorithm's convergence behavior, stability, benefits, and drawbacks. The important query, though, is what benchmarks should be utilized for a given set of problems. All algorithms must therefore exert the same amount of computational effort in order to be fair, which is typically accomplished by limiting the number of function evaluations. The fourth concern is that the computational time must be same to compare the performance of algorithms. It seems to reason that even a poor algorithm may be able to produce acceptable results if given a lot more time to run than the others. The fifth concern is that how to most effectively scale up algorithms that solve small-scale problems to effectively handle truly large-scale, practical problems. These issues are discussed for the future directions of the research.
3	Wang et al. 2021	This study presents an organized review of the literature on the nature-inspired method in logistics. Logistics includes the planning, monitoring, and control of product storage between the levels of use and manufacture. They divided the articles into three categories: forwarding logistics, reverse logistics, and integrated logistics. In conventional forward logistics, raw materials are often purchased from suppliers and then turned into completed goods. Following that, distributioncentreprovide these products to customers in order to satisfy their wants. Reverse logistics are used to process the flow of returned goods from customers back to gathering points. Since developing reverse and forward logistics separately results in suboptimal plans in relation to supply chain objectives, the two must be combined. Both vertical and horizontal integration can be used to describe this process. The first type consists of a mix of activities that are in the same planning stage. Five important algorithms have been studied in this study: artificial bee colony, genetic algorithm, memetic algorithm, ant colony optimization, and particle swarm optimization. The outcomes of actual case studies show that the PSO is capable of handling actual reverse logistics issues

		in international search areas. They can observe that, so far, hybrids of genetic algorithms have proven to be the most effective. In order to optimize the logistics and select a suitable distribution, it is imperative to conduct research on the logistics distribution route optimization, employing cutting-edge, nature-inspired algorithms.
4	Tzanetos and Dounias 2021	This study tried to describe NIA and also to examine whether there is an actual requirement to continue on proposing new similar approaches in literature. This study proposed the creation of a database with well-known standard benchmarks for comparing the effectiveness of NI algorithms as a crucial step for the near future. The necessity of unreasonably introducing new nature-inspired intelligent (NII) algorithms in literature is also questioned, and the potential negative effects of NII algorithms encountered in literature are examined. In an effort to reduce the deceptive appearance of metaheuristic variation as nature-inspired optimization algorithms, rules for the creation of new nature-inspired algorithms are also put forward. In order to assess the significance and potential of each NI technique, the applications of the NI algorithms to real-world issues were examined in this research.
5	Rai et al. 2022	This study provide an in-depth review of the novel NIA developed in 2019-2021.The most important challenges that come throughout the development of multi-thresholding model of an image based on NIA are presented in their review. Their study focuses on new NIA and multi-level thresholding (MLT) applications during the past three years (2019–2021).
6	Muazu et al. 2022	NIA that emerged between 2001 and 2021, including the Ebola optimization algorithm, the Corona virus optimization algorithm, and others is described in this paper. The purpose of this study is to present a review of these algorithms and their use in their current state and for future inspiration in the area of connective t-way testing for improved optimization. They give brief knowledge about NIA and divide them into four classes: evolution-inspired technique, swarm-inspired technique, human-inspired technique, and physics-inspired technique. Some future research direction is given in this study for the use of recently developed metaheuristic like season optimization (SO), Tree growth algorithm (TGA), corona virus optimization algorithm (COA), Tunicate swarm algorithm (TSA) etc. for solving combinatorial t-way optimization difficulty, use of nature stimulated metaheuristic algorithm in image segmentation difficulty, engineering problem, feature assortment problems, initiate a privacy problem in connective t-way testing.
7	S.S. Vinod Chandra and H.S. Anand 2022	This paper gives a brief overview of computing models influenced by nature, hybrid metaheuristic models, and hyper heuristic models. This study shows a major involvement in constructing a hyper heuristics technique from metaheuristic techniques for any common problem field. Traditional and non-traditional (new generation) metaheuristic algorithms have also well described in this paper. Here, nature-inspired computing models are partitioned in three computing models inspired by bio, evolution and swarm-based. The basic inspiration of hyperheuristics is to build up new techniques by joining known heuristics. Heuristic selection and heuristic generation are two main categories of hyper-heuristics. The main objective of hyperheuristics is to increase computational speed, results that are sensibly understandable, reliable in quality, notable and good presentation across a broad scale of problems that divide ordinary features. An uncomplicated hill climbing example using dual heuristic is given in this paper to show how the performance can be enhanced using hyperheuristic.

In between 2019 to 2022 there are many new NIA algorithms which were developed. Researchers have used some engineering problems along with benchmark functions to prove their algorithms better as compared to others. So far, we could not find any research paper which can tell which algorithm is best for which type of problem. Our review helps to identify commonly used engineering problems and compare the results of all newly developed algorithms together. This review will help research to identify one single/few NIA algorithm which is performing better as compared to all other algorithms used on particular engineering problem.

3 Comparative analysis

Our aim for writing this review paper is to find some algorithms which can be used more efficiently for some real-life optimization problems. For this purpose, we studied all newly developed algorithms from 2019 to 2022 and try to find out some common real world optimization problems. In this section, we have provided a comparative analysis of all algorithms used for those real-life problems and tried to find most efficient and suitable algorithms for these problems. We found eight common engineering problems from 79 research papers mentioned in Table 1 which includes(i) design of a welded beam (ii)design of a spring (iii) design of a pressure vessel (iv)design of a cantilever beam (v) design of a I beam (vi) rolling element bearing (vii) speed reducer(viii)3-bar truss design. Many algorithms have been used in these eight engineering problems. We have listed all algorithms and compared the performance of each algorithm for each engineering problem. The mathematical results for optimal design of several engineering problems uses a 30 independent optimization runs in the optimization process. The parameters selected by them are population size, iteration and run time. Majorly most of the researchers have taken population size ranging between 20 to 100, iteration either 500 or 1000 and run time 30.

Design of a welded beam problem

The goal of this problem is to decrease the welded cost of a welded beam. The constraints are as follow:

1. Sheer stress (μ)
2. Bending stress in the beam (θ)
3. Bucking load on the block (B_c)
4. End deflection of the beam (Υ)
5. Side constraints

This problem includes four variables likebreadth of weld (h), the length of the connected part of the block (l) height of the block (t) and the thickness of the block (b).

The mathematical formulation is as follow:

Consider$\vec{t} = [\, t_1 t_2 t_3\, t_4 \,] = $ [a b c d]
Minimize f $(\vec{t}\,) = 1.10471\, t_1^2 t_2 + 0.04811\, t_3 t_4\, (14.0 + t_2)$,
Subject to

$$y_1(\vec{t}) = \mu\,(\vec{t}) - \mu_{\max} \le 0$$
$$y_2(\vec{t}) = \varphi\,(t) - \varphi_{\max} \le 0$$
$$y_3(\vec{t}) = \Upsilon\,(\vec{t}) - \Upsilon_{\max} \le 0$$
$$y_4(\vec{t}) = t_1 - t_4 \le 0$$
$$y_5(\vec{t}) = T - B_c\,(\vec{x}) \le 0$$
$$y_6(\vec{t}) = 0.125 - t_1 \le 0$$
$$y_7(\vec{t}) = 1.10471\, t_1^2 + 0.04811\, t_3 t_4 (14.0 + t_2\,) - 5.0 \le 0$$

Variable range$0.1 \le t_1 \le 2, 0.1 \le t_2 \le 10,\ 0.1 \le t_3 \le 10, 0.1 \le t_4 \le 2$

Where $\mu(\vec{t}) = \sqrt{(\mu')^2 + 2\mu'\mu''\frac{t_2}{2R} + \mu''^2}$

$$\mu' = \frac{T}{\sqrt{2}t_1 t_2}$$
$$\Upsilon(\vec{t}) = \frac{4Tl^3}{Et_3^2 t_4}$$
$$\varphi(\vec{t}) = \frac{6TX}{t_4 t_3^2}$$
$$\mu'' = \frac{UV}{W}$$
$$U = T(X + \frac{t_2}{2})$$
$$V = \sqrt{\frac{t_2^2}{4} + (\frac{t_1 + t_3}{2})^2}$$
$$W = 2\{\sqrt{2}t_1 t_2[\frac{t_2^2}{4}(\frac{t_1 + t_3}{2})^2]\}$$
$$B_c(\vec{t}) = \frac{4.013E\sqrt{\frac{t_3^2 t_4^6}{36}}}{X^2}(1 - \frac{t_3}{2X}\sqrt{\frac{E}{4G}})$$

$T = 6000lb,\ X = 14in.,\ \Upsilon_{max} = 0.25in.,\ E = 30 \times 10^6 psi$

Out of 79 research papers, 41 researchers have worked on same problem. Table 3 shows the comparative analysis of all 41 algorithms for a (thickness of the weld), b (length of the attached part of the bar), c (height of the bar), d (thickness of the bar) and found that AO method is giving minimum cost out of all NIA algorithms.

Table 3 Result of different algorithms for design of a welded beam problem

Sr. No.	Algorithms	a	b	c	D	Optimum cost
1	BOA	0.1736	2.9690	8.7637	0.2188	1.6644
2	HHO	0.2040	3.5311	9.0275	0.2061	1.7313
3	HGSO	0.2054	3.4476	9.2060	0.2060	1.7260
4	MPA	0.2057	3.4705	9.0366	0.2057	1.7249
5	PFA	0.2057	3.4705	9.0366	0.2057	1.7249
6	SFO	0.2038	3.6630	9.0506	0.2064	1.7323
7	SOA	0.2054	3.4723	9.0352	0.2011	1.7235
8	SMA	0.2054	3.2589	9.0384	0.2058	1.6960
9	BWO	0.1987	3.4217	9.0286	0.2001	1.6638
10	MRFO	0.2057	3.4705	9.0366	0.2057	1.7249
11	WSA	0.2057	3.4705	9.0366	0.2057	1.7249
12	MGA					1.6729
13	BOA	0.2057	3.4705	9.0366	0.2057	1.7249
14	NRO					1.7248
15	DTBO	0.2057	3.4705	9.0366	0.2057	1.7249
16	POA	0.2057	3.4701	9.0383	0.2057	1.7250
17	HPO	0.1988	3.3377	9.1920	0.1988	1.6702
18	EO	0.2057	3.4705	9.0366	0.2057	1.7249
19	RSO	0.2053	3.4657	9.0345	0.2010	1.7220
20	PO					1.7249
21	AEO	0.2057	3.4705	9.0366	0.2057	1.7249
22	SOA	0.2054	3.4723	9.0352	0.2011	1.7235
23	AOS	0.2057	3.4705	9.0366	0.2057	1.7249
24	FDA	0.2055	3.2578	9.0366	0.2057	1.6955
25	AO	0.1631	3.3652	9.0202	0.2067	1.6566
26	AVOA	0.2057	3.4705	9.0366	0.2057	1.7249
27	AOA	0.1945	2.5709	10.0000	0.2018	1.7164
28	CSA	0.2057	3.4705	9.0366	0.2057	1.7249
29	AOA	0.2057	3.4705	9.0366	0.2057	1.7249
30	TSO	0.2057	3.4704	9.0334	0.2057	1.7248
31	QANA	0.2057	3.4705	9.0366	0.2057	1.7249
32	ROA	0.2001	3.3658	9.0112	0.2069	1.7064
33	HGS	0.2600	5.1025	8.0396	0.2600	2.3021
34	RSA	0.1446	3.514	8.9251	0.21162	1.6726
35	BO	0.2057	3.4705	9.0366	0.2057	1.7249
36	PDO	0.1963	3.4932	9.0856	0.2070	1.6882
37	PPF	0.2056	3.2547	9.0366	0.2057	1.6953
38	CBOA					1.7246
39	POA	0.2025	3.5429	9.0334	0.2061	1.7323

40	GOA	0.1810	3.7550	9.0367	0.2057	1.6957

Design of a Tension/compression spring problem:

The aim of this problem is to get the lowest weight of a design tension/compression spring problem. The constraints are described as lowest deflection/shear stress and surge frequency together with design variables as well asmean coin diameter (c), wire diameter (w) and numeral of active coils (a).

The mathematical formulation of the problem is as follow:

Consider $\vec{t} = [\,t_1 t_2 t_3\,] = [\text{w c a}]$

Minimize $f(\vec{t}) = (t_3 + 2)\, t_2 t_1^2$

Subject to $y_1(\vec{t}) = 1 - \frac{t_2^3 t_3}{71785 t_1^4} \leq 0$

$$y_2(\vec{t}) = \frac{4t_2^2 - t_1 t_2}{12566(t_2 t_1^3 - t_1^4)} + \frac{1}{5108 t_1^2} \leq 0$$

$$y_3(\vec{t}) = 1 - \frac{140.45}{t_2^3 t_3} \leq 0$$

$$y_4(\vec{t}) = \frac{t_1 + t_2}{1.5} - 1 \leq 0$$

Variable range$0.05 \leq t_1 \leq 2, 0.25 \leq t_2 \leq 1.30, 2 \leq t_3 \leq 15$

Out of 79 research papers, 38 researchers have worked on the same problem. We have compared the optimum cost of each 38 algorithms in table 4 for coin diameter (c), wire diameter (w) and numeral of active coils (a).The AO method shows the optimal weight out of all.

Table 4 Result of different algorithms on design of a spring problem

Sr. No.	Algorithms	w	c	a	Optimal weight
1	BOA	0.0513	0.3349	12.9227	0.0120
2	GBO	0.0520	0.3651	10.8146	0.0127
3	HHO	0.0518	0.3593	11.1389	0.0126
4	HGSO	0.0518	0.3569	11.2023	0.0126
5	MPA	0.0517	0.3576	11.2392	0.0127
6	PFA	0.0517	0.3576	11.2357	0.0127
7	SOA	0.0511	0.3429	12.0085	0.0126
8	BWO	0.0511	0.3430	12.0914	0.0126
9	BOA	0.0516	0.3558	11.3418	0.0127
10	AEO	0.0519	0.3618	10.8798	0.0127
11	PO				0.0128
12	MRFO	0.5223	0.3733	10.3831	0.0126
13	SOA	0.0511	0.3429	12.0875	0.0127
14	EO	0.0516	0.3550	11.3879	0.0126
15	POA	0.0518	0.3616	11.0079	0.0126
16	POA	0.0516	0.3559	11.3312	0.0126
17	MGA				0.0126
18	HPO	0.0517	0.3579	11.2153	0.0126
19	AOS	0.0517	0.3567	11.2883	0.0127
20	FDA	0.0517	0.3579	11.2224	0.0127
21	AO	0.0502	0.3526	10.5425	0.0112
22	AVOA	0.0517	0.3563	11.3161	0.0127
23	AOA	0.0500	0.3498	11.8637	0.0121

24	CSA	0.0518	0.3589	11.1650	0.0127
25	AOA	0.0508	0.3348	11.7020	0.0127
26	QANA	0.0519	0.3624	10.9616	0.0127
27	BO	0.0517	0.3566	11.2933	0.0127
28	RSO	0.0511	0.3420	12.0667	0.0127
29	SFOA	0.0519	0.3613	11.0280	0.0127
30	PDO	0.0517	0.3582	11.2038	0.0127
31	PPF	0.0518	0.3588	11.1562	0.0126
32	CBOA				0.0127
33	GOA	0.1344	1.1676	14.2742	3.6619
34	RSA	0.0578	0.5848	4.0167	0.0118
35	TSO	0.0516	0.3556	11.3542	0.0127
36	WHO				0.0126
37	CSBO	0.0517	0.3577	11.2312	0.0127
38	NRO				0.0127

Design of Pressure vessel

In design of pressure vessel, we reduce the manufacture cost and it contains four constraints, four parameters and four variables $t_1$tot_4:

$S_t(t_1$, width of the shell), $H_t(t,$ width of the head), M (t_3, internal radius), N (t_4, length of the component without head).

The mathematical model of this problem is as follow:

Consider $\vec{t} \;=\; [t_1 t_2 t_3\, t_4\,] = [S_t\; H_t\; M\; N\,]$
Minimize$f(\vec{t}) = 0.6224 t_1 t_3 t_4 \;+ 1.7781 t_2\, t_2^3 + 3.1661 t_1^2\; t_4 \;+ 19.84 t_1^2\; t_3\,,$
Subject to

$$y_1(\vec{t}) = -t_1 + 0.0193\; t_3 \le 0$$
$$y_2(\vec{t}) = -t_3 + 0.00954\; t_3 \le 0$$
$$y_3(\vec{t}) = -\Pi t_3^2 t_4 - \frac{4}{3}\Pi t_3^3 + 1{,}296{,}000 \le 0$$
$$y_4(\vec{t}) = -t_4 - 240 \le 0$$

Variable range $0 \le t_1 \le 99$, $0 \le t_2 \le 99$, $10 \le t_3 \le 200$, $10 \le t_4 \le 200$

Out of 79 research papers 37 researchers have worked on the same problem. We have compared the optimum cost of each 37 algorithms in table 5 for S_t (width of the shell), H_t (width of the head), M (internal radius), N (length of the component without head).The PDO method shows the optimal cost out of all.

Table 5 Performance of dissimilar algorithms for solving design of a Pressure vessel problem

Sr. No.	Algorithms	S_t	H_t	M	N	Optimum cost
1	HHO	0.8176	0.4373	42.0917	176.7196	6000.4620
2	MPA	0.7782	0.3846	40.3196	199.9990	5885.3350
3	PFA	0.7782	0.3846	40.3196	199.9900	5885.3351
4	SOA	0.7781	0.3832	40.3152	200.0000	5879.5241
5	SMA	0.7931	0.3932	40.6711	196.2178	5994.1857
6	MRFO	0.7787	0.3849	40.3446	199.6515	5886.2000
7	PO					5908.0250
8	LCBO	1.2569	0.6187	65.1248	10.4330	5320.0000

9	AEO	0.8374	0.4139	43.3896	161.2685	6820.8007
10	SOA	0.7781	0.3832	40.3151	200.0000	5878.4521
11	AOS	0.7787	0.3853	40.3409	199.7215	5888.4579
12	EO	0.8125	0.4375	42.0984	176.6365	6059.7143
13	AO	1.0540	0.1828	59.6219	38.8050	5949.2258
14	BWO	0.7778	0.3731	39.9973	199.9361	5796.0389
15	HPO	0.7781	0.3846	40.3196	200.0000	5885.3327
16	POA	0.8291	0.4098	42.9605	167.0972	5999.4001
17	MGA					6059.7143
18	DTBO	0.7786	0.3853	40.3428	199.5782	5885.3550
19	POA	0.7780	0.3846	40.3126	199.9972	5883.0278
20	AVOA	0.7790	0.3850	40.3603	199.4342	5886.6765
21	AOA	0.8304	0.4162	42.7513	169.3454	6048.7844
22	CSA	12.4507	6.1544	40.3196	200.0000	5885.3327
23	AOA	0.7900	0.3899	41.0226	199.4405	5900.0000
24	QANA	0.7782	0.3846	40.3196	200.0000	5885.3328
25	ROA	0.7296	0.2227	40.4323	198.5537	5311.9175
26	BOA	0.7783	0.3848	40.3263	199.9210	5886.1681
27	BO	0.8125	0.4375	42.0984	176.6366	6059.7144
28	RSO	0.7760	0.3831	40.3133	200.0000	5878.5395
29	SFOA	0.7782	0.3847	40.3200	200.0000	5886.8000
30	PDO	0.7938	0.2539	49.0582	105.9976	4527.2000
31	DOX	0.7782	0.3848	40.3150	200.0000	5885.5700
32	CBOA					5883.1170
33	GOA	0.5479	0.2469	43.4967	160.0482	4527.5000
34	RSA	0.8401	0.4190	43.3817	161.5556	6034.7591
35	TSO	0.7782	0.3846	40.3196	199.9999	5885.3327
36	CSBO	0.8125	0.4375	42.0984	1.7664	6059.7143
37	NRO					5835.3327

Cantilever beam problem

The cantilever beam is built from five components, each component containa vacant cross section with stable thickness. There is outer force performing at the open end of the cantilever. The mass of the beam is to be reduced while the higher limit is assigning on the vertical displacement of the free end. The devise variables are the width or height, x_i of the cross section of each component. The problem is formulated mathematically using classical beam theory are as follow:

Minimize fitness $= 0.0624 \times (u_1 + u_2 + u + u_4 + u_5)$

Subject to

$$g(x) = \frac{61}{u_1^3} + \frac{37}{u_2^3} + \frac{19}{u_3^3} + \frac{7}{u_4^3} + \frac{1}{u_5^3} - 1$$

Variable ranges

$$0.01 \leq u_1, u_2, u_3, u_4, u_5 \leq 100$$

Out of 79 research papers 15 researchers have worked on same problem. We have compared the optimum cost of each 15 algorithms in table 6 for u_1, u_2, u_3, u_4, u_5 (height of five hollow square blocks with constant thickness) and found PDO method shows the optimal cost out of all.

Table 6 Performance of different algorithms for solving problem of design of a cantilever beam

Sr. No	Algorithms	u_1	u_2	u_3	u_4	u_5	Optimum cost
1	GBO	6.0124	5.3129	4.4941	3.5036	2.1506	1.3400
2	PFA	6.0155	5.3090	4.4946	3.5018	2.1528	1.3400
3	SAR	6.0161	5.3092	4.4941	3.5016	2.1526	1.3400
4	SMA	6.0178	5.3109	4.4936	3.5011	2.1050	1.3400
5	WSA	5.9759	4.8808	4.4654	3.4778	2.1392	1.3033
6	BOA	5.9696	4.8871	4.4615	3.4753	2.1458	1.3066
7	LCBO	6.0237	5.3008	4.4977	3.4892	2.1559	1.3400
8	AEO	6.0289	5.3165	4.4626	3.5084	2.1578	1.3400
9	AO	5.8881	5.5451	4.3798	3.5973	2.1026	1.3390
10	PDO	5.6896	5.0208	4.2617	3.3130	2.0409	1.3004
11	PPF	6.0206	5.2922	4.4983	3.5221	2.1363	1.3363
12	AEO	6.0289	5.3165	4.4626	3.5084	2.1577	1.3399
13	RSA	6.0231	5.4457	4.2770	3.5853	2.1767	1.3386
14	HPO	6.0055	5.3059	4.4947	3.5134	2.1542	1.3365
15	MGA	6.0117	5.3157	4.5107	3.4857	2.1503	1.3400

Problem of design of I beam

The objective of this problem is to minimize the vertical deflection of the beam depend on correlated parameters. The design of I beamisfocus to two devise constraints: stress and the load's cross-sectional area. This problem contain four design variables are as follows: the width of the flange's(v), the height of component (u), the thickness of the web's$(W_{t,})$, and the thickness of the flange's(F_t).

The formulation of the difficulty is as follow:

$$Minimize\ fitness = \frac{5000}{\frac{1}{12}W_{t,}(v-2F_t)^3 + \frac{1}{6}uF_t^3 + 2uF_t(\frac{v-F_t}{2})^2}$$

Subject to:

$$y_1(x) = 2uF_t + W_{t,}(v-2F_t)^3 \leq 300$$

$$y_2(x) = \frac{180000x_1}{W_t(v-2F_t)^3 + 2uF_t[4F_t^2 + 3v(v-F_t)]} + \frac{15000\,x_2}{(v-2F_t)W_t^3 + 2F_tu^3} \leq 6$$

The variables are subject to:
$10 \leq v \leq 80$, $10 \leq u \leq 50$, $0.9 \leq W_{t,} \leq 5$, $0.9 \leq F_t \leq 5$

Out of 79 research papers 8 researchers have worked on the same problem. We have compared the optimum cost of each 8 algorithms in table 7 for width of the flange's(v), the height of component (u), the thickness of the web's$(W_{t,})$, and the thickness of the flange's(F_t) and found that ROA shows the optimal weight.

Table 7 Performance of different algorithms on problem of design of the I beam

Sr. No.	Algorithms	v	u	W_t	F_t	Optimal weight
1	GBO	50.0000	80.0000	0.9000	2.3217	0.0131
2	SFO	50.0000	80.0000	1.7637	5.0000	0.0066
3	SAR	80.0000	50.0000	0.9000	2.3218	0.0131
4	SMA	49.9988	79.9943	1.7647	4.9997	0.0066

5	ROA	50.0000	80.0000	1.7600	5.0000	0.0059
6	HGS	50.0000	80.0000	0.9000	2.3218	0.0131
7	MGA	49.9999	79.9999	0.9000	2.3217	0.0130
8	PDO	80.0000	50.0000	0.9000	2.3218	0.0131

Rolling element bearing

The aim of this engineering problem is to maximize the carrying capacity of dynamic load of a rolling element bearing in so far as possible. Outcomes of this difficulty included 10 decision variables like diameter of a ball (B_b), diameter of a pitch (B_m), total number of balls (n), curvature coefficients of inner (X_i) and outer (X_0) raceway, $K_{G_{min}}, K_{G_{max}}, \mu,\ \nu,\ \boldsymbol{\varphi}$. The mathematical expression of this difficulty given below:

$$Maximize z = \{ \begin{matrix} F_c \times n^{2/3} \times B_b^{1.8} & if B_{b \leq 25.4} \\ 3.647 \times F_c \times n^{2/3} \times B_b^{1.4} & otherwise \end{matrix} \}$$

Subjectto :

$$h_1(\vec{x}) = \frac{\theta_0}{2\sin^{-1}(\frac{B_b}{B_m})} - n + 1 \leq 1,$$

$$h_2(\vec{x}) = 2B_b - K_{G_{min}}(G - g) \geq 0$$
$$h_3(\vec{x}) = K_{G_{max}}(G - g) - 2B_b \geq 0$$
$$h_4(\vec{x}) = \varphi W_b - B_b \leq 0$$
$$h_5(\vec{x}) = B_m - 0.5 \times (G + g) \geq 0$$
$$h_6(\vec{x}) = B_m - (0.5 + \nu) \times (G + g) - B_m \geq 0$$
$$h_7(\vec{x}) = 0.5(G - B_m - B_b) - \mu B_b \geq 0$$

$$h_8(\vec{x}) = X_i \geq 0.515 ,$$

$$h_9(\vec{x}) = X_0 \geq 0.515$$

Where

$$F_c = 37.91[1 + \left(\frac{1+\sigma}{1-\sigma}\right)^{1.72} (\frac{X_i(2X_0 - 1)}{X_o(2X_1 - 1)})^{0.41}{}^{10/3}]^{-0.3} \times \left[\frac{\sigma^{0.3}(1-\sigma)^{1.39}}{(1+\sigma)^{1/3}}\right] \times [\frac{2X_i}{2X_i - 1}]^{0.41}$$

$$k = [\left\{\frac{G-g}{2} - 3\left(\frac{L}{4}\right)\right\}^2 + \left\{\frac{G}{2} - \frac{L}{4} - B_b\right\}^2 - \{\frac{g}{2} + \frac{L}{4}\}^2]$$
$$l = 2\left\{\frac{G-g}{2} - 3\left(\frac{L}{4}\right)\right\} \times \{\frac{G}{2} - \frac{L}{4} - B_b\}$$
$$\theta_0 = 2\Pi - \cos^{-1}(\frac{k}{l})$$

$W_b = 30,\ G = 160,\ g = 90,\ u_i = u_0 = 11.033,\ \sigma = \frac{B_b}{B_m},\ X_i = \frac{u_i}{B_b},\ X_o = \frac{u_0}{B_b},\ L = G - g - 2B_b,\ 0.15 \leq (G - g) \leq B_b \leq 0.45,\ 4 \leq n \leq 50,\ 0.515 \leq X_i, X_0 \leq 0.60,\ 0.4 \leq K_{G_{min}} \leq 0.5,\ 0.6 \leq K_{G_{max}} \leq 0.7,\ 0.3 \leq \mu \leq 0.4,\ 0.02 \leq \nu \leq 0.1,\ 0.6 \leq \varphi \leq 0.85$

Out of 79 research papers 15 researchers have worked on the above problem. We have compared the optimum cost of each 41 algorithms in table 8 for diameter of a ball (B_b), diameter of a pitch (B_m), total number of balls (n), curvature coefficients of inner (X_i) and outer (X_0) raceway curvature coefficient, $K_{G_{min}}, K_{G_{max}}, \mu,\ \nu,\ \boldsymbol{\varphi}$ .The ROA method shows the optimal cost out of all.

Table 8 Performance of different algorithms to solve Rolling element bearing problem

Sr. No.	Algorithms	B_b	B_m	X_i	X_0	n	$K_{G_{min}}$	$K_{G_{max}}$	μ	ν	φ	Optimal cost
1	GBO	21.8750	125.0000	0.5150	0.5150	11.2882	0.4148	0.6287	0.3000	0.0203	0.6721	85245.0611
2	HHO	21.0000	125.0000	0.5150	0.5150	11.0921	0.4000	0.6000	0.3000	0.0505	0.6000	83011.8833
3	SOA	21.4189	125.0000	0.5150	0.5150	10.9412	0.4000	0.7000	0.3000	0.0200	0.6000	85068.0520
4	MRFO	21.4255	125.7190	0.5150	0.5150	11.0000	0.4051	0.6906	0.6926	0.3000	0.0537	85549.2390
5	HBO	21.4230	125.7194	0.5150	0.5150	11.0000	0.4881	0.6794	0.3000	0.0690	0.6082	85532.5700

6	AEO	21.4256	125.7189	0.5150	0.5150	11.0000	0.4102	0.6384	0.3000	0.0470	0.6095	85549.0559
7	SOA	21.4190	125.0000	0.5150	0.5150	10.9411	0.4000	0.7000	0.3000	0.0200	0.6000	85068.8570
8	AVOA	21.4233	125.7227	0.5150	0.5150	11.0012	0.4044	0.6187	0.3000	0.0691	0.6025	85539.1579
9	CSA	21.4180	125.0000	0.5150	0.5150	11.3560	0.4000	0.7000	0.3000	0.0200	0.6120	85201.6410
10	ROA	22.0660	127.4109	0.5250	0.5252	11.9023	0.4078	0.6116	0.3058	0.0260	0.6117	87971.8530
11	RSO	21.4177	125.0000	0.5150	0.5150	10.9403	0.4000	0.7000	0.3000	0.0200	0.6000	85069.0210
12	RSA	21.2973	125.1722	0.5153	0.5178	10.8852	0.4125	0.6323	0.3019	0.0244	0.6024	83486.6400
13	WHO											14614.1357
14	HPO	21.8750	125.0000	0.5150	0.5157	10.7770	0.4000	0.7000	0.3000	0.0290	0.6000	83918.4925
15	MGA	21.8745	125.0003	0.5150	0.5150	10.7171	0.4059	0.6556	0.3000	0.0775	0.6000	83912.8798

Speed reducer problem

The main objective is to minimize the weight of speed reducer in so far as possible through subject to constraints:

- Gear teeth under bending stress

- Surface stress

- Shafts transverse deflections

- Stresses in the shafts

The problem of speed reducer contain seven design variables ($u_1 to\ u_7$) named as width of the face (u_1), a set of teeth(u_2), total number of pinion teeth (u_3), initial shaft distance between bearing(u_4), second shaft distance between bearing(u_5), first shaft diameter(u_6) and second shaft diameter(u_7).

$$Minimize\ z = 0.7854u_1u_1^2 \times (3.3333 \times u_3^2 + 14.9334 \times u_3 - 43.0934) - 1.508 \times (u_6^2 + u_7^2)$$

Subject to

$$t_1(\vec{u}) = \frac{27}{(u_1u_2^2 \times u_3)} - 1 \le 0$$
$$t_2(\vec{u}) = \frac{397.5}{(u_1u_2^2 \times u_3^2)} - 1 \le 0$$
$$t_3(\vec{u}) = \frac{1.93u_4^3}{(u_2u_3 \times u_6^4)} - 1 \le 0$$

$$t_4(\vec{u}) = \frac{1.93u_5^3}{(u_2u_3 \times u_7^4)} - 1 \le 0$$

$$t_5(\vec{u}) = \frac{1}{110 \times u_6^3} \times \sqrt{\left(\frac{745u_4^2}{u_2u_3}\right) + 16.9 \times 10^6} - 1 \le 0$$
$$t_6(\vec{u}) = \frac{1}{85 \times u_7^3} \times \sqrt{\left(\frac{745u_5^2}{u_2u_3}\right) + 157.5 \times 10^6} - 1 \le 0$$
$$t_7(\vec{u}) = \frac{u_2u_3}{40} - 1 \le 0$$
$$t_8(\vec{u}) = \frac{5u_2}{u_1} - 1 \le 0$$
$$t_9(\vec{u}) = \frac{u_1}{12u_2} - 1 \le 0$$

$$t_{10}(\vec{u}) = \frac{1.5u_6 + 1.9}{u_4} - 1 \le 0$$
$$t_{11}(\vec{u}) = \frac{1.1u_7 + 1.9}{u_5} - 1 \le 0$$
$2.6 \le u_1 \le 3.6$, $0.7 \le u_2 \le 0.8$, $17 \le u_3 \le 28$, $7.3 \le u_4 \le 8.3$, $7.8 \le u_5 \le 8.3$, $2.9 \le u_6 \le 3.9$, $5.0 \le u_7 \le 5.5$

Out of 79 research papers 24 researchers have worked on same problem. We have compared the optimum cost of each 24 algorithms in table 9 for width of the face (u_1), a set of teeth(u_2), total number of pinion teeth (u_3), initial shaft distance between bearing(u_4), second shaft distance between bearing(u_5), first shaft diameter(u_6) and second shaft diameter(u_7) and found FDA method best among all.

Table 9 Performance of several algorithms for solving the problem of speed reducer.

Sr. No.	Algorithms	u_1	u_2	u_3	u_4	u_5	u_6	u_7	Optimum cost
1	GBO	3.4999	0.7000	17.0000	7.3000	7.8000	3.3502	5.2866	2996.3481
2	HGSO	3.4980	0.7100	17.0200	7.6700	7.8100	3.3600	5.2890	2997.1000
3	SOA	3.5016	0.7000	17.0000	7.3000	7.8000	3.3342	5.2416	2992.9985
4	MRFO	3.5000	0.7000	17.0000	7.3000	7.7153	3.3502	5.2866	2994.4711
5	HBO	3.5000	0.7000	17.0000	7.3000	7.7153	3.3502	5.2867	2994.4711
6	PO								2994.4711
7	AEO	3.5000	0.7000	17.0000	7.3000	7.7153	3.3502	5.2867	2994.4711
8	SOA	3.5010	0.7000	17.0000	7.3000	7.8000	3.3342	5.2653	2993.4521
9	AOS	3.5000	0.7000	17.0000	7.3000	7.7150	3.3500	5.2866	2994.4458
10	FDA	3.5000	0.7000	17.0000	7.3000	7.8000	2.9000	5.0450	2749.5830
11	AO	3.5020	0.7000	17.0000	7.3090	7.7476	3.3641	5.2994	3007.7300
12	AOA	3.5038	0.7000	17.0000	7.3000	7.7293	3.3564	5.2860	2997.9157
13	CSA	3.5000	0.7000	17.0000	7.3000	7.7153	3.3502	5.2866	2994.4700
14	AOA	3.4976	0.7000	17.0000	7.3000	7.8000	3.3501	5.2857	3000.0000
15	BO	3.5000	0.7000	17.0000	7.3000	7.7150	3.3502	5.2865	2994.3810
16	RSO	3.5010	0.7000	17.0000	7.3000	7.8000	3.3230	5.2457	2993.0027
17	PDO	3.4978	0.7000	17.0000	7.3001	7.8007	3.3511	5.2965	2999.5000
18	CBOA								2994.1000
19	GOA	3.5000	0.7000	17.0000	7.3000	7.7000	3.3494	5.2879	2996.0010
20	SSA								2996.7077
21	RSA	3.5028	0.7000	17.0000	7.3081	7.7472	3.3507	5.2877	2996.5157
22	POA	3.5000	0.7000	17.0000	7.3000	7.8000	3.3502	5.2867	2996.3482
23	HPO	3.2412	0.7000	17.0000	7.3000	7.7153	3.3502	5.2867	2892.7292
24	MGA								2994.4389

Three bar truss design problem

The three-bar truss design problem is considered as one of the essential engineering problem, which focuses to find the smallest value under constraints such as bending, stress and bucking. This difficulty contains two decision variables, together with the region of the first, second and third bar.

The third bar truss problem is expressed mathematically as follow:

$$Minimize\ Fitness\ (\vec{x}) = (2\sqrt{2}x_{B_1} + x_{B_2}) \times u$$

$$t_1(\vec{x}) = \frac{\sqrt{2}x_{B_1} + x_{B_2}}{\sqrt{2}x_{B_1}^2 + 2x_{B_1}x_{B_2}}L - \sigma \leq 0$$
$$t_2(\vec{x}) = \frac{x_{A_2}}{\sqrt{2}x_{B_1}^2 + 2x_{B_1}x_{B_2}}L - \sigma \leq 0$$
$$t_3(\vec{x}) = \frac{1}{\sqrt{2}x_{B_2} + x_{B_1}}L - \sigma \leq 0$$
$$0 \leq x_{B_1}x_{B_2} \leq 1$$
$$u = 100\,cm,\ L = \frac{2KN}{cm^2},\ \sigma = \frac{2KN}{cm^2}$$

Out of 79 research papers 18 researchers have worked on the same problem. After comparing the results for x_{B_1}(area of the first and third bar) and x_{B_2} (area of the second bar) in table 10 we found that PDO method performs better for the above-mentioned problem.

Table 10 Performance of different algorithms for solving the problem of a 3- bar truss design.

Sr. No.	Algorithms	x_{B_1}	x_{B_2}	Optimum weight
1	GBO	0.7887	0.4082	263.8958
2	HHO	0.7887	0.4083	263.8958
3	SFO	0.7885	0.4089	263.8959
4	WSA	0.7887	0.4082	263.8958
5	AEO	0.7887	0.4082	263.8959
6	FDA	0.7887	0.4083	263.8958
7	AO	0.7926	0.3966	263.8684
8	AVOA	0.7887	0.4082	263.8958
9	AOA	0.7937	0.3943	263.9154
10	QANA	0.7887	0.4082	263.8958
11	ROA	0.7887	0.4082	263.8958
12	PDO	0.2195	0.1884	106.9300
13	WHO			263.8958
14	PPF	0.7861	0.4068	263.4634
15	RSA	0.7887	0.4081	263.8928
16	CSBO	0.7887	0.4082	263.8958
17	HPO	0.7886	0.4083	263.8958
18	MGA			263.8958

4. Discussion

NIA are stochastic investigation techniques, can move about to any convoluted search space and situate optimal (near optimal) solutions in suitable computational time. They can present solutions to every complex optimization difficulty that is not easily solved by the predictable nonlinear programming (NLP) techniques because of their nature that may involve point of discontinuities of the search domain, non-differentiable objective functions, unfocused advice and values of the function. The algorithm discovered over the last four years is presented in this study with their brief description. We have tried to find out some best NIA to solve real world optimization problems. For this purpose, we have found eight engineering problems and take the common algorithms for each problem from table 1 to compare the performance of these algorithms. After analyzing their performance from table 3 to table 10, the results are concluded in table 11.

Table 11 Best algorithm for real life engineering problems

Algorithm	Problems
AO	Design of welded beam and design of tension/compression spring

FDA	Speed reducer problem
ROA	Design of I beam and problem of rolling element bearing
PDO	Design of a pressure vessel, cantilever beam and 3-bar truss

Table 12 shows some commonly used unimodal and multimodal benchmark functions which are used in all 79 research paper to check the efficiency of their algorithms.

Table 12 Unimodal and multimodal benchmark function

F1	$f(x)=\sum_{i=1}^{n} x_i^2$
F2	$f(x)=\sum_{i=0}^{n}\lvert x_i\rvert+\prod_{i=0}^{n}\lvert x_i\rvert$
F3	$F(x)=\sum_{i=1}^{d}(\sum_{j=1}^{i} x_j)^2$
F4	$f(x)=max\{\lvert x_i\rvert, 1\le i\le n\}$
F5	$f(x)=\sum_{i=1}^{n-1}\left[100\left(x_i^2-x_{i+1}\right)^2+(1-x_i)^2\right]$
F6	$f(x)=\sum_{i=1}^{n}([x_i+0.5)])^2$
F7	$f(x)=\sum_{i=0}^{n} ix_i^4+random[0,1)$
F8	$f(x)=\sum_{i=1}^{n}(-x_i^2\sin\left(\sqrt{\lvert x_i\rvert}\right))$
F9	$f(x)=[x_i^2-10\cos(2\Pi x_i)+10]$
F10	$f(x)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\Pi x_i)\right)+20+e$
F11	$f(x)=1+\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})$
F12	$f(x)=\frac{\Pi}{n}\{10sin\ (\Pi y_1)\}+\sum_{i=1}^{n}(y_i-1)^2[1+10sin^2(\Pi y_{i+1})+\sum_{i=1}^{n}u(x_i,10,100,4)], where\ y_i = 1+\frac{x_{i+1}}{4}, u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m if\ x_i>a\\ 0\ if-a\le x_i\ge a\\ k(x_i-a)^m-a\le x_i\end{cases}$
F13	$f(x)=0.1\left(sin^2(3\Pi x_1)\right)+\sum_{i=1}^{n}(x_i-1)^2+[1+sin^2(3\Pi x_i+1)]+(x_n-1)^2+sin^2(2\Pi x_n)+\sum_{i=1}^{n}u(x_i,5,100,4)$

A little bit more analysis has been done considering those 4 algorithms mentioned in table 11. Since all these algorithms have also been solved using benchmark problems so their average and standard deviation are compared for solution of 13 benchmark problems mentioned in table 12. (Rezaei et al. 2022). The run time has been taken as 30.

Table 13 Comparison of ROA and AO for average and standard deviation for Dimension (D) =100 on 13 benchmark function.

	ROA for D=100 (iteration 500, population size 30)		AO for D= 100 (iteration 500, population size 30)	
Benchmark function	Average	S.D	Average	S.D
F1	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F2	0.00E+00	0.00E+00	5.09E-217	0.00E+00
F3	1.84E-209	0.00E+00	0.00E+00	0.00E+00
F4	1.21E-171	0.00E+00	2.51E-219	0.00E+00
F5	2.70E+01	4.59E-01	2.47E-02	4.27E-02
F6	3.43E-02	8.11E-05	5.43E-04	9.29E-04
F7	1.13E-05	5.68E-05	8.95E-04	7.03E-04
F8	2.61E+03	4.74E+01	-9.91E+03	2.45E+03
F9	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F10	8.88E-16	0.00E+00	8.88E-16	0.00E+00
F11	0.00E+00	0.00E+00	0.00E+00	0.00E+00
F12	1.16E-03	7.21E-03	7.33E-06	8.70E-06

F13	2.40E-02	8.76E-02	1.84E-05	1.65E-05

Table 14 Comparison of FDA, AO and PDO for average and standard deviation for D=100 on 13 benchmark function.

	FDA for D=100 (iteration 1000, population size 30)		AO for D= 100 (iteration 1000, population size 30)		PDO for D=100 (iteration 1000, population size 50)	
Benchmark function	Average	S.D	Average	S.D	Average	S.D
F1	9.24E+01	2.75E+01	6.65E+02	3.76E+02	0.00E+00	0.00E+00
F2	1.25E+01	1.29E+01	6.24E+01	1.07E+01	0.00E+00	0.00E+00
F3	5.14E+04	1.22E+04	6.29E+05	3.33E+05	0.00E+00	0.00E+00
F4	5.71E+01	3.26	6.41	1.09	0.00E+00	0.00E+00
F5	2.64E+04	1.07E+04	7.10E+05	2.37E+05	98.98E+00	0.004E+00
F6	4.24E+07	2.04E+05	4.70E+07	1.10E+06	20.64E+00	3.02E+00
F7	1.83	2.31E-01	5.96E-02	8.17E-02	1.28E-06	1.26E-05
F8	-4.00E+04	2.82E+03	-4.00E+04	5.02E+03	-14.69E+00	1270.30E+00
F9	4.87E+02	5.68E+01	6.47E+01	2.40E+01	0.00E+00	0.00E+00
F10	1.97E+01	2.61E-01	9.20	8.72E-01	0.00E+00	0.00E+00
F11	1.99E+01	8.78	2.09E+02	2.52E+02	0.00E+00	0.00E+00
F12	1.29E+03	1.40E+03	9.23E+02	2.73E+03	0.29E+00	0.23E+00
F13	4.10E+10	0.00E+00	4.75E+10	1.56E+10	9.81E+00	5.00E+00

The yellow color in the table shows the best optimal result. After comparing the results of table 13 and 14 we found that AO and PDA give us comparatively better results.

We also have shown details of Journal name, Author name, impact factor and citation of all 79 review papers in table 15. Serial Number. 43, 47, 48 and 73 are the details of NIA algorithms ROA (IF 8.665, Citation 66) FDA (IF 7.18, Citation 63), AO (IF 7.18, Citation 744) and PDA (IF 5.10 and Citation 41).

So overall these four algorithms were found to be suitable for solving above mentioned 8 real life engineering problems.

Table 15 Detail of 79 review papers in terms of Author name, Journal name, Impact factor and citation.

S.No.	Paper name	Author Name	Journal name	Impact factor	Citation
1	Harris hawks optimization: Algorithm and applications	Heidari et al. 2019	Future Generation Computing Systems	7.187	2466
2	The Sailfish Optimizer: A novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems	Shadravan et al. 2019	Engineering Applications of Artificial Intelligence	7.802	292
3	A New Meta-Heuristic Optimizer: Pathfinder Algorithm	Yapici and Cetinkaya 2019	Applied Soft Computing Journal	8.263	186
4	Seagull Optimization Algorithm: Theory and its Applications for Large Scale Industrial Engineering Problems	Dhiman and Kumar 2019	Knowledge-Based Systems	8.139	552
5	A Novel Optimization Booster Algorithm	Pakzad-Moghaddam et al. 2019	Computers & Industrial Engineering	7.18	12

6	Henry gas solubility optimization: a novel physics-based algorithm	Hashim et al. 2019	Future Generation Computer Systems	7.307	503
7	Sea Lion Optimization Algorithm	Masadeh et al. 2019	International Journal of Advanced Computer Science and Applications	1.092	151
8	The naked mole-rat algorithm	Salgotra and Singh 2019	Neural Computing and Applications	5.102	91
9	Nuclear Reaction Optimization: A novel and powerful physics-based algorithm for global optimization	Wei et. al. 2019	IEEE Access	4.34	52
10	Atom search optimization and its application to solve a hydrogeologic parameter estimation proble	Zhao et al. 2019	Knowledge-Based Systems	8.139	319
11	A New Optimization Algorithm Based on Search and Rescue Operations	Shabani et. al. 2019	Mathematical Problems in Engineering	1.43	75
12	Wildebeest herd optimization: A new global optimization algorithm inspired by wildebeest herding behaviour	Amali and Dinakaran 2019	Journal of Intelligent & Fuzzy Systems	1.737	20
13	Butterfly optimization algorithm: a novel approach for global optimization	Arora and Singh 2019	Soft Computing	4.2	804
14	The blue monkey: A new nature inspired metaheuristic optimization algorithm	Mahmood and Al-Khateeb 2019	Periodicals of Engineering and Natural Sciences	1.162	9
15	Emperor Penguins Colony: a new metaheuristic algorithm for optimization	Harif et. al. 2019	Evolutionary Intelligence	2.96	106
16	Future search algorithm for optimization	Elsisi 2019	Evolutionary Intelligence	2.96	33
17	Chimp Optimization Algorithm	Khishe and Mosavi 2020	Expert Systems With Applications	8.665	394
18	Slime Mould Algorithm: A New Method for Stochastic Optimization	Li et al. 2020	Future Generation Computer Systems	7.307	1185

19	Gradient-Based Optimizer: A New Metaheuristic Optimization Algorithm	Ahmadianfar et al. 2020	Information Sciences	8.233	302
20	Marine Predators Algorithm: A Nature-inspired Metaheuristic	Faramarzi et al. 2020	Expert Systems With Applications	8.665	829
21	A mayfly optimization algorithm	Zervoudakis and Tsafarakis 2020	Computers & Industrial Engineering	7.18	301
22	Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications	Zhao et al. 2020	Engineering Applications of Artificial Intelligence	7.802	415
23	Billiards-inspired optimization algorithm; a new meta-heuristic method	Kaveh et al. 2020	Structures	4.01	48
24	Equilibrium optimizer: A novel optimization algorithm	Faramarzi et al. 2020	Knowledge-Based Systems	8.139	921
25	Coronavirus Optimization Algorithm: A Bioinspired Metaheuristic Based on the COVID-19 Propagation Model	Martínez-Álvarez et al. 2020	Big Data	10.835	87
26	A novel swarm intelligence optimization approach: sparrow search algorithm	Xue and Shen 2020	Systems Science & Control Engineering	2.8	767
27	Sandpiper optimization algorithm: a novel approach for solving real-life engineering problems	Kaur, Jain and Goel 2020	Applied Intelligence	5.086	32
28	Black Widow Optimization Algorithm: A novel meta-heuristic approach for solving engineering optimization problems	Hayyolalam and Kazem 2020	Engineering Applications of Artificial Intelligence	7.802	343
29	FBI inspired meta-optimization	Chou and Nguyen 2020	Applied Soft Computing Journal	8.263	73
30	Novel meta-heuristic bald eagle search optimisation algorithm	Alsattar et al. 2020	Artificial Intelligence Review	9.588	203

31	A novel life choice-based optimizer	Khatri et al. 2020	Soft Computing	3.732	24
32	Parameters optimization of support vector machines for imbalanced data using social ski driver algorithm	Tharwat and Gabel 2020	Neural Computing and Applications	5.102	77
33	Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm	Zhao et al. 2020	Neural Computing and Applications	5.102	188
34	Heap-based optimizer inspired by corporate rank hierarchy for global optimi- zation	Askari et al. 2020	Expert Systems with Applications	8.665	156
35	Color harmony algorithm: an art-inspired metaheuristic for mathematical function optimization	Zaeimi and Ghoddosian 2020	Soft Computing	3.732	23
36	Stochastic paint optimizer: theory and application in civil engineering	Kaveh et al. 2020	Engineering with Computers	8.083	42
37	Political Optimizer: A novel socio-inspired meta-heuristic for global optimizatio	Askari et al. 2020	Knowledge-Based Systems	8.139	208
38	Water strider algorithm: A new metaheuristic and applications	Kaveh et al. 2020	Structures	4.01	102
39	A new Newton metaheuristic algorithm for discrete performance-based design optimization of steel moment frames	Gholizadeh et al. 2020	Computers and Structures	5.372	62
40	Giza Pyramids Construction: an ancient-inspired metaheuristic algorithm for optimization	Harif et al. 2021	Evolutionary Intelligence	2.96	50
41	Gaining-sharing knowledge based algorithm for solving optimization problems: a novel nature-inspired algorithm	Mohamed et al. 2020	International Journal of Machine Learning and Cybernetics	4.377	185
42	African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems	Abdollahzadeh et al. 2021	Computers & Industrial Engineering	7.18	282

43	Remora optimization algorithm	Jia et al. 2021	Expert Systems With Applications	8.665	66
44	Chameleon Swarm Algorithm: A bio-inspired optimizer for solving engineering design problems	Braik 2021	Expert Systems With Applications	8.665	95
45	Artificial gorilla troops optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems	Abdollahzadeh et al. 2021	International Journal of Intelligent Systems	8.709	235
46	Coronavirus herd immunity optimizer (CHIO)	Al-Betar et al. 2021	Neural Computing and Applications	5.102	108
47	Flow Direction Algorithm (FDA): A Novel Optimization Approach for Solving Optimization Problems	Karami et. al. 2021	Computers & Industrial Engineering	7.18	63
48	Aquila Optimizer: A novel meta-heuristic optimization algorithm	Abualigah et. al. 2021	Computers & Industrial Engineering	7.18	744
49	QANA: Quantum-based avian navigation optimizer algorithm	Zamani et al. 2021	Engineering Applications of Artificial Intelligence	7.802	70
50	Atomic orbital search: A novel metaheuristic algorithm	Azizi 2021	Applied Mathematical Modelling	5.336	91
51	The Arithmetic Optimization Algorithm	Abualigah et. al. 2021	Computer Methods in Applied Mechanics and Engineering	6.588	934
52	Dingo Optimizer: A Nature-Inspired Metaheuristic Approach for Engineering Problems	Bairwa et al. 2021	Mathematical Problems in Engineering	1.43	29
53	The Red Colobuses Monkey: A New Nature–Inspired Metaheuristic Optimization Algorithm	Al-Kubaisy et al. 2021	International Journal of Computational Intelligence Systems	2.259	12
54	Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems	Hashim et. al. 2021	Applied Intelligence	5.019	344

55	A novel algorithm for global optimization: Rat Swarm Optimizer	Dhiman et.al. 2021	Journal of Ambient Intelligence and Humanized Computing	3.662	171
56	Hunger games search: Visions, conception, implementation, deep analysis, perspectives, and towards performance shifts	Yang et al. 2021	Expert Systems With Applications	8.665	410
57	Horse herd optimization algorithm: A nature-inspired algorithm for high-dimensional optimization problems	Miar et al. 2021	Knowledge-Based Systems	8.139	110
58	Preaching-inspired swarm intelligence algorithm and its applications	Wei et. al. 2021	Knowledge-Based Systems	8.139	18
59	Battle royale optimization algorithm	Rahkar 2021	Neural Computing and Applications	5.102	81
60	Cat and Mouse Based Optimizer: A New Nature-Inspired Optimization Algorithm	Dehghani et al. 2021	Sensors	3.847	29
61	Tuna Swarm Optimization: A Novel Swarm-Based Metaheuristic Algorithm for Global Optimization	Xie et. al. 2021	Computational Intelligence and Neuroscience	3.12	42
62	Past present future: a new human-based algorithm for stochastic optimization	Naik and Satapathy 2021	Soft Computing	3.732	11
63	Aptenodytes Forsteri Optimization: Algorithm and applications	Yang et. al. 2021	Knowledge-Based Systems	8.139	16
64	A new evolutionary algorithm: Learner performance based behavior algorithm	Rahman and Rashid 2021	Egyptian Informatics Journal	4.195	40
65	Material Generation Algorithm: A Novel Metaheuristic Algorithm for Optimization of Engineering Problems	Talatahari et al. 2021	Processes	3.352	43
66	Child Drawing Development Optimization Algorithm Based on Child's Cognitive Development	Abdulhameed and Rashid 2022	Arabian Journal for Science and Engineering	2.807	18

67	Bonobo optimizer (BO): an intelligent heuristic with self-adjusting parameters over continuous spaces and its applications to engineering problems	Das and Pratihar 2022	Applied Intelligence	5.019	33
68	Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer	Abualigah et. al. 2022	Expert Systems With Applications	8.665	326
69	A new human-based metaheuristic algorithm for solving optimization problems on the base of simulation of driving training process	Dehghani et al. 2022	Scientifc Reports	4.379	10
70	Pelican Optimization Algorithm: A Novel Nature-Inspired Algorithm for Engineering Applications	Trojovský and Dehghani 2022	Sensors	3.847	45
71	Circulatory System Based Optimization (CSBO): an expert multilevel biologically inspired metaheuristic algorithm	Ghasemi et al. 2022	Engineering Applications of Computational Fluid Mechanics	8.391	4
72	The cheetah optimizer: a nature-inspired metaheuristic algorithm for large-scale optimization problems	Akbari et al.2022	Scientifc Reports	4.379	5
73	Prairie Dog Optimization Algorithm	Ezugwu et al. 2022	Neural Computing and Applications	5.102	41
74	Gazelle optimization algorithm: a novel nature-inspired metaheuristic optimizer	Agushaka et al. 2022	Neural Computing and Applications	5.102	6
75	Mountain Gazelle Optimizer: A new Nature-inspired Metaheuristic Algorithm for Global Optimization Problems	Abdollahzadeh et al. 2022	Advances in Engineering Software	4.255	3
76	A new human-based metahurestic optimization method based on mimicking cooking training	Trojovská and Dehghani 2022	Scientifc Reports	4.379	5
77	Hunter–prey optimization: algorithm and applications	Naruei and Sabbagh 2022	Soft Computing	3.732	18

78	A novel swarm intelligence algorithm inspired by the grazing of sheep	Kivi and Majidnezhad 2022	Journal of Ambient Intelligence and Humanized Computing	3.662	12
79	Wild horse optimizer: a new meta-heuristic algorithm for solving engineering optimization problems	Naruei and Keynia 2022	Engineering with Computers	8.083	87

5 Application of NIA

NIA are widely used in all types of real-life problems and some of the applications of NIA are mentioned in Figure 2. Application of NIA is classified in health care, environment, industrial, commercial, machine learning and smart city in this figure.

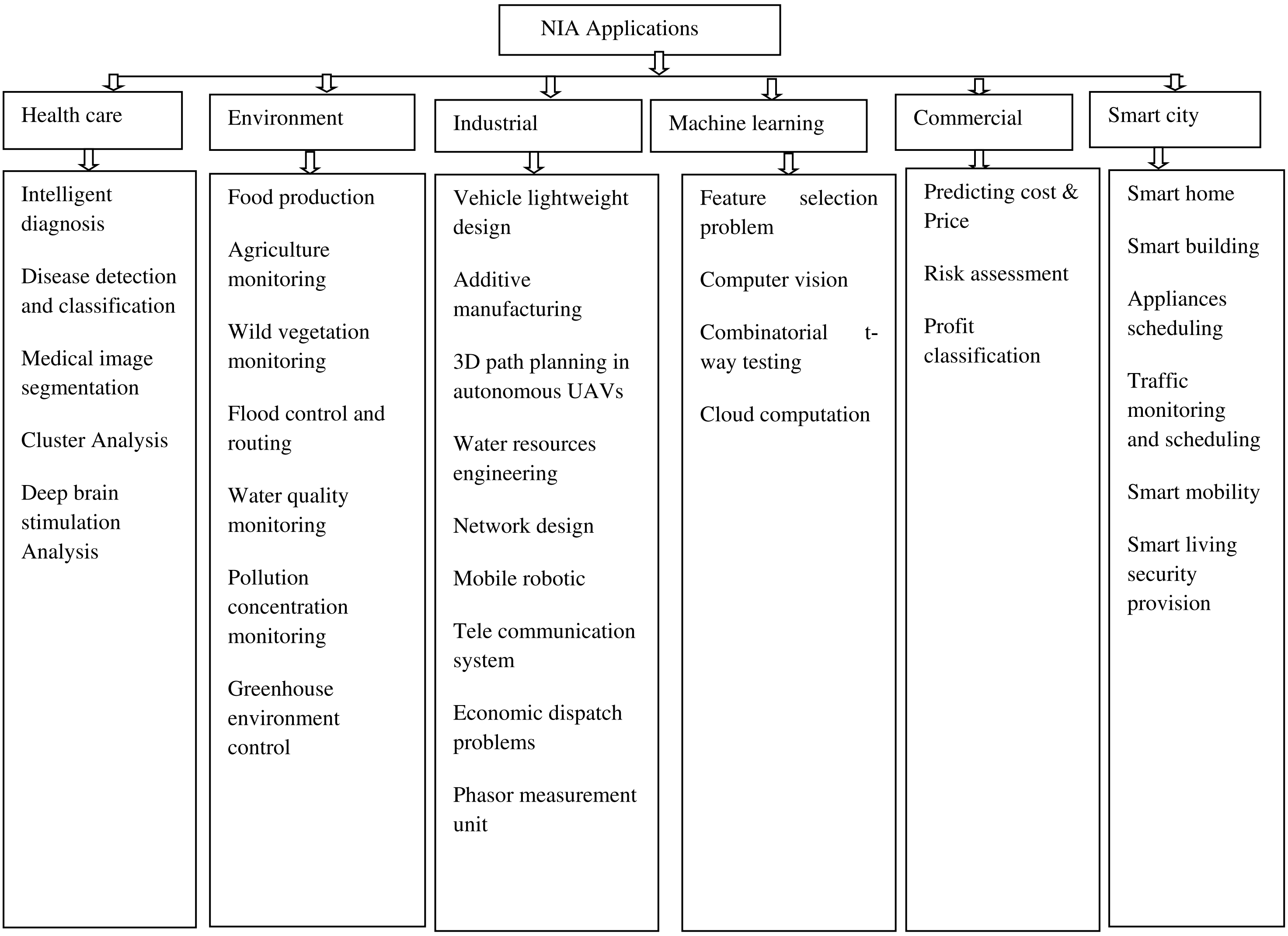

Fig.2 classification of application of NIA

6 Future research direction in nature inspired algorithm.

The researchers are developing new algorithms based on their research type of problem but there is a strong need to combine all these algorithms and compare the results of all together as it will save future researchers time and their research will proceed in right direction. Our paper is an attempt to review all available papers thoroughly from 2019 to 2022 and conclude some results from them.

The outcome of different population sizes on the presentation of the NIA should be analyzed.

NIA can be developed by combining machine learning techniques to solve different software engineering and multi objective optimization problems like feature selection problem, signal denoising, neural network, unmanned aerial vehicle (UAV) mission planning problem.

NIA can be applied on some less explored areas such as temporary load forecasting, stock market prediction, spam recognition, weather prediction etc.

Improving the accuracy and reducing the number of chosen features are two objectives that are considered in most of the papers for checking the performance of algorithm. Besides these objectives computational time, complexity, scalability, and stability in more than one objective in feature selection can be used as an objective.

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