# Efficient Improved Henry Gas Solubility<br>
Optimization and Its Application in Feature<br>
Selection Problems<br>
Jiayin Wang, Ronghe Zhou, Yukun Wang\*, and Zhongfeng Li<br> *Abstract*—The henry gas solubility optimization algorithm **before the sum of the meta-heuristic spired by Henry's law. While if<br>a meta-heuristic algorithm is problem and the sum of the sum of** enry Gas Solubility<br>pplication in Feature<br>Problems<br>in Wang\*, and Zhongfeng Li<br>tion problems involving multiple variables and constraints.<br>These algorithms are able to search in high-dimensional<br>spaces and find optimal solu Efficient Improved Henry Gas Solubility<br>
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problems, it does face certain l Exploration and School is a meta-heuristic algorithm inspired by Henry's law. While it and a explorithms are spaces and find optimization problems, it does face certain limitations such as insufficient proplems, it does f Abstract—The henry gas solubility optimization algorithm is**<br>
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propolems, it does face certain l **show the context of the search is the search in the search in the search the search in this partial and solven is a meta-heuristic algorithm inspired by Henry's law. While it has demonstrated effectiveness in solving vari** a mena-neurism approxim inspired by remiv is awe. While the effectiveness in solving various optimization<br>problems, it does face certain limitations such as insufficient appropriate meta-algorithms so<br>population diversity, **Endamination** and encouver the search in some that the endamination subset about the search in this paper, we propose an enhanced population diversity, and slow convergence speed when dealing characteristics of the with c provisms, it couss are ecret wan imitations such as instincted<br>population diversity, and slow convergence speed when dealing<br>with complex problems. In this paper, we propose an enhanced<br>state increases. (4) M<br>as E\_HGSO. Fi pouration unversity, and sow convergence speed when dealing the propose and enhanced<br>
with complex problems. In this paper, we propose an enhanced<br>
section of henry gas solubility optimization algorithm, known<br>
techniques. **Example the ELEGSO** algorithm, we provided a comparison with eight and the E-HGSO algorithm, we conducted a comparison of the eight parametering in a single range, while we introduce a new proprimization algorithm, known **Example the CEC2017** benchmark functions. The results and Wilcom-<br> **algorithms on the ability of avoiding easy to fall into local**<br> **algorithms** perform well in dealing<br> **algorithms on the concept of a search factor to st SEVENCY FIG. We miroute a new group search formula and search of a search factor to strike a balance between**<br> **of improve the ability of avoiding easy to fall into local**<br> **of the concept of a search factor to strike a b** For the analy of a search and more to the analy of a search and more in the concept of a search factor to strike a balance between exploration and exploitation. Second, we introduce a position and independence update formu Furthermore, we applied E.HGSO to the feature selection<br>the process. Finally, we propose a new worst gas position<br>and independence<br>exploration and exploitation. Second, we introduce a position<br>and independence<br>update formu **Problem.** The results indicate that a basance between<br>the results include a position and exploration and exploration. Second, we introduce a position and independence<br>update formula to enhance the diversity and randomness **Exploration and exploration. Second, we introduce a position**<br> **the distribution is the search process. Finally, we propose a new worst gas position** optimization proble<br>
update formula with a Lévy flight mechanism. This update formula to emfance the urversity and randominess or the unger<br>search process. Finally, we propose a new worst gas position<br>update formula with a Lévy flight mechanism. This mechanism<br>enhances the gas search's abilit date formula with a Levy flight mechanism. I his mechanism<br>
ances the gas search's ability to addifferent distance<br>
quirements within the search space, leading to improved<br>
the Friedman test and Wilcoxon rank sum test indi ennances the gas search s ability to adapt to unterent d<br>requirements within the search space, leading to im<br>search efficiency and accuracy. To evaluate the effective<br>the E\_HGSO algorithm, we conducted a comparison wi<br>algo the search space, leading to improved<br>accuracy. To evaluate the effectiveness of<br>m, we conducted a comparison with eight<br>C2017 benchmark functions. The results<br>provided a comparison with eight<br>and Wilcoxon rank sum test in EXECT and convertion and Wilcox and Microsofter and Microsofter and Microsofter and Microsofter and Microsofter and Microsofter and the results in the resu hms on the CEC2017 benchmark functions. The results<br>
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The results indicates and Wilcoxon rank sum test indicate that<br>
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Manuscript received April 22, 2024; revised July 26, 2024. This working the solutionary and Evolutionary and Evolutionary and Evolutionary Media Evolutions simulate nature and human intelligence to search interval Evolutio Example 11 INTRODUCTION<br>
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more popular algo **TV L**loyed for solving global optimization problems. These<br>algorithms simulate nature and human intelligence to search<br>for optimal solutions. These algorithms exhibit several key<br>characteristics: (1) Suitable for solving gorithms simulate nature and human intelligence to search<br>
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Manuscript received April 22, 2024; revised July 26, 2024. This work<br>was supported by Liaoning Provincial Joint Funds Project of China (Gran<br>No. 2023-MSLH-323).<br>Jiayin Wang is a postgraduate student of School of Electronic Jiayin Wang is a postgraduate student of Schoolnformation Engineering, University of Science and Te<br>Anshan, Liaoning 114051, PR China; (e-mail: wangjy<br>Ronghe Zhou is a PhD Candidate of School of Ele-<br>tion Engineering, Univ

enry Gas Solubility<br>pplication in Feature<br>Problems<br>in Wang\*, and Zhongfeng Li<br>tion problems involving multiple variables and constraints.<br>These algorithms are able to search in high-dimensional<br>spaces and find optimal solu **SPACE SPACE THEORY**<br> **SPACE SPACE THEORY**<br> **Problems**<br>
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appropriate me tion problems involving multiple variables and constraints.<br>These algorithms are able to search in high-dimensional<br>spaces and find optimal solutions. (2) Highly flexible, with<br>appropriate meta-algorithms selectable based tion problems involving multiple variables and constraints.<br>These algorithms are able to search in high-dimensional<br>spaces and find optimal solutions. (2) Highly flexible, with<br>appropriate meta-algorithms selectable based tion problems involving multiple variables and constraints.<br>These algorithms are able to search in high-dimensional<br>spaces and find optimal solutions. (2) Highly flexible, with<br>appropriate meta-algorithms selectable based These algorithms are able to search in high-dimensional<br>spaces and find optimal solutions. (2) Highly flexible, with<br>appropriate meta-algorithms selectable based on the specific<br>characteristics of the problem. (3) Faster c spaces and find optimal solutions. (2) Highly flexible, with<br>appropriate meta-algorithms selectable based on the specific<br>characteristics of the problem. (3) Faster convergence and<br>shorter solution times compared to altern appropriate meta-algorithms selectable based on the specific<br>characteristics of the problem. (3) Faster convergence and<br>shorter solution times compared to alternative optimization<br>techniques. (4) Meta-heuristic optimizatio characteristics of the problem. (3) Faster convergence and<br>shorter solution times compared to alternative optimization<br>techniques. (4) Meta-heuristic optimization algorithms<br>perform well in dealing with non-linear problems shorter solution times compared to alternative o<br>techniques. (4) Meta-heuristic optimization<br>perform well in dealing with non-linear problem<br>able to find globally optimal or near-optimal s<br>using diverse search strategies. chiniques. (4) Meta-heuristic optimization algorithms<br>from well in dealing with non-linear problems. They are<br>le to find globally optimal or near-optimal solutions by<br>ing diverse search strategies. Additionally, the flexib perform well in dealing with non-linear problems. They are<br>able to find globally optimal or near-optimal solutions by<br>using diverse search strategies. Additionally, the flexibility<br>and independence from gradients of meta-h able to find globally optimal or near-optimal solutions by<br>using diverse search strategies. Additionally, the flexibility<br>and independence from gradients of meta-heuristic<br>algorithms provide them with an advantage in solvi using diverse search strategies. Additionally, the flexibility<br>and independence from gradients of meta-heuristic<br>algorithms provide them with an advantage in solving global<br>optimization problems. When compared to tradition d independence from gradients of meta-heuristic<br>gorithms provide them with an advantage in solving global<br>timization problems. When compared to traditional<br>timization methods like simulated annealing algorithm,<br>ta-heuristi algorithms provide them with an advantage in solving global<br>optimization problems. When compared to traditional<br>optimization methods like simulated annealing algorithm,<br>meta-heuristic algorithms excel in finding optimal so

of the Friedman test and Wilcoxon rank sum test indicate that<br>
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sproblem. The results indicate that E\_HGSO performs competi-<br>
discussions **Extreme in the example E-HGSO to the teature selection**<br> **Examplementally intelligence the selection**<br> **Examplement intelligence the solution-based and convergence precision.**<br> **Examplementally arons solutionly also solu** Meta-heuristic optimization algorithms are widely emp-<br>
Mith the continuous exploration of natural evolution-based<br>
algorithms simulate nature and human intelligence to search<br>
algorithms shows been proposed, among which s complemization problems. When compared to traditional<br>optimization problems. When compared to traditional<br>optimization methods like simulated annealing algorithm,<br>meta-heuristic algorithms excel in finding optimal solution eptimization methods like simulated annealing algorithm,<br>meta-heuristic algorithms excel in finding optimal solutions<br>by simulating nature and human intelligence, which makes<br>them particularly effective in tackling complex penarization inclusion and simulated unitarial equilibrius the share of the meta-heuristic algorithms excel in finding omplex optimization by simulating nature and human intelligence, which makes them particularly effectiv mean-means and human intelligence, which makes<br>by simulating nature and human intelligence, which makes<br>them particularly effective in tackling complex optimization<br>problems [1].<br>Meta-heuristic optimization algorithms can by simulating italite and initial intelligence, winch inacts<br>them particularly effective in tackling complex optimization<br>problems [1].<br>Meta-heuristic optimization algorithms can be classified<br>into four main categories: Ev mem patuculary enective in tacking complex opunization<br>problems [1].<br>Meta-heuristic optimization algorithms can be classified<br>foroup mitelligence based algorithms. Human based<br>algorithms, Physics and chemity based algorith problems [1].<br>
Meta-heuristic optimization algorithms can be classified<br>
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algorithms, Physics and chemistry based algorithms.<br>
Evolution-based algorithms are m Meta-heuristic optimization algorithms can be classified<br>into four main categories: Evolution-based algorithms,<br>Group intelligence based algorithms, Human based<br>algorithms, Physics and chemitry based algorithms.<br>Evolutionmto four mann categories: Evolution-based algorithms,<br>Group intelligence based algorithms, Human based<br>algorithms, Physics and chemistry based algorithms.<br>Evolution-based algorithms are mainly designed to<br>achieve the overa Group intenigence based aigorithms, Human based<br>algorithms, Physics and chemistry based algorithms.<br>Evolution-based algorithms are mainly designed to<br>achieve the overall progress of the group and ultimately<br>acomplete the o argoriums, Physics and chemistry based argoriums.<br>
Evolution-based algorithms are mainly designed to<br>
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(Da Evolution-based algorithms are mainly designed to<br>achieve the overall progress of the group and ultimately<br>complete the optimal solution by simulating the<br>evolutionary law of superiority and inferiority in nature<br>(Darwin's meve the overall progress of the group and ultimately<br>mplete the optimal solution by simulating the<br>olutionary law of superiority and inferiority in nature<br>olution(OE) [3] are the main representatives.<br>ith the continuous e complete the optimal solution by simulating the<br>
evolutionary law of superiority and inferiority in nature<br>
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Differential Evolution (DE) [3] are the main representatives.<br> evolutionary law of superiority and inferiority in nature<br>(Darwin's law). The Genetic Algorithm (GA) [2] and<br>Differential Evolution (DE) [3] are the main representatives.<br>With the continuous exploration of natural evolutio (Darwin's law). The Genetic Algorithm (GA) [2] and<br>Differential Evolution (DE) [3] are the main representatives.<br>With the continuous exploration of natural evolution-based<br>algorithms by scientists, various evolutionary op Differential Evolution (DE) [3] are the main representatives.<br>With the continuous exploration of natural evolution-based<br>algorithms have been proposed, among which some of the<br>more popular algorithms are Evolutionary Orti

more popular algorithms annality matrix and the method method is several key<br>
for optimal solutions. These algorithms exhibit several key<br>
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Manuscript received April 22, 2024; revised July 26, 2024. This Coloring Solutions, These and Coloring and Kindel and Coloring Programming (GEP) [Continentations: The Evolutionary Programming (GEP) [Continentation Strategies Manuscript received April 22, 2024; revised July 26, 2024. Th Programming(GEP)<br>
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Jintelligence of the School of Electronic and<br>
Jintelligence of the Somoniain Engineering, University of Science and Technology Liaon No. 2023-MSLH-323). Intelligence of the growing is a postgraduate student of School of Electronic and solution. In such algorify and the and rechnology Liaoning, Anshan, Liaoning 114051, PR China; (e-mail: wangiy\_97@163.co win ine continuous exploration of natural evolution-based<br>algorithms by scientists, various evolutionary optimization<br>algorithms have been proposed, among which some of the<br>more popular algorithms are Evolutionary Strategi algorithms by scientists, various evolutionary optimization<br>algorithms have been proposed, among which some of the<br>more popular algorithms are Evolutionary Strategies (ES)<br>[4], Evolutionary Programming (EP) [5], Gene Expre algorithms have been proposed, among which some of the<br>more popular algorithms are Evolutionary Strategies (ES)<br>[4], Evolutionary Programming (GP) [6], Govariance Matrix Adaptive<br>Evolutionary Strategies (CMA-ES) [7], Bioge more popular algorithms are Evolutionary Strategies (ES)<br>[4], Evolutionary Programming (EP) [5], Gene Expression<br>Programming (GEP) [6], Covariance Matrix Adaptive<br>Evolutionary Strategies (CMA-ES) [7], Biogeography<br>Based Op [4], Evolutionary Programming (EP) [5], Gene Expression<br>Programming (GEP) [6], Covariance Matrix Adaptive<br>Evolutionary Strategies (CMA-ES) [7], Biogeography<br>Based Optimization (BBO) [8] and so on.<br>Group intelligence optimi Programming  $(GE)$  [0], Covariance Matrix Adaptive<br>Evolutionary Strategies  $(CMA-ES)$  [7], Biogeography<br>Based Optimization (BBO) [8] and so on.<br>Group intelligence optimization algorithms use the<br>intelligence of the group to a Evolutionary Strategies (CMA-ES) [7], Biogeography<br>Based Optimization (BBO) [8] and so on.<br>
Group intelligence optimization algorithms use the<br>
intelligence of the group to achieve the global optimal<br>
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Group intelligence optimization algorith<br>
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is a its of intelligent optimization algorithms proposed (MHOSO) algorithm for<br>based on human behaviou: Teaching-Learning-Based in DNA genome sequence<br>Optimization (TLBO) [17], Tabu Search Algorithm (TS) detecting the targ based on numan benaviour: Teading-Learning-Based in DNA genome sequence<br>
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[18], League Championship Algorithm (LCA) [19], Secker introduced a new the Henry<br>
Algorithm (EMA) [21], Group Counselling Optimization propo [18], League Championsin (SOA) [20], Exchared a new the Freduced a new the CoBL/HGSO based on Higorithm (SOA) [21], Group Counselling Optimization proposed a SVR-base of Algorithm (GCO) [22], Social Learning optimization ( Optimization Aigorithm (SOA) [20], Exchange Market (OBL/HOSO) based on inversel<br>Algorithm (GCO) [22], Group Counselling Optimization proposed a SVR-based pred<br>Algorithm (GCO) [22], Social Learning optimization (SLO) Solubi Algorithm (EMA) [21], Group Counselling Optimization proposed a SVK-based p<br>
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Support vector regression in<br> Algorithm (GCO) [22], Social Learning optimization (SLO)<br>
[23], Cultural Evolution Algorithm (CEA) [24], Volleyball support vector regression mention<br>
Premier League Algorithm (VPL) [25].<br>
The problems by using physical a [23], Cutural Evolution Algorithm (CEA) [24], Volleyball<br>Premier League Algorithm (VPL) [25].<br>Physics and chemistry based algorithms focus on solving<br>problems by using physical and chemical principles to<br>simulate the beha multiple and chemistry based algorithm (VPL) [25].<br>
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bblems by using physical and chemical principles to the same time updating<br>
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Gravitatio chemistry, engineering and some of the more popular<br>algorithms are: Simulated Amealing (SA) [26], the exploration performational Local Search (GLSA) [27], Big-bang named QHGSO.<br>Big-Crunch (BBBC) [28], Gravitational Search algorithms are: Simulated Annealing (SA) [20], the exploration performance<br>Gravitational Local Search (GLSA) [27], Big-bang med QHGSO.<br>Big-Crunch (BBBC) [28], Gravitational Search Algorithm HGSO algorithm exhibits<br>(GSA) [2 Gravitational Local Seren (GLSA) [27], Big-onig named QrtGSO.<br>
Big-Crunch (BBBC) [28], Gravitational Search Algorithm HGSO algorithm exhibits<br>
(GSA) [29], Central Force Optimization (CFO) [30], across various fields; howe Big-Crimen (BBBC) [28], Gravitational Search Algorithm FIGSO algorithm exhibits (GSA) [30], Central Force Optimization (CFO) [30], across various fields; however Direction Algorithm (GbSA) [31], Flow challenges including s (USA) [29], Central Force Optimization (CFO) [30], across various fielas; noweve<br>Glaax)-based-Search Algorithm (GbSA) [31], Flow challenges including susception<br>Direction Algorithm [32]. sluggish convergence speed.<br>It is w Granday-based-search Angorium (GoSA) [31], Frow challenges inculting subseque specified in the state of the state optimization algorithm capable of perfectly solving all types increasing increasing optimization algorithm c borecom Algorium [32].<br>
It is widely achowledged that there is no universal<br>
optimization algorithm capable of perfectly solving all types<br>
algorithm often leads to<br>
of optimization problems. Because the characteristics a It is widely acknowledged that there is no unversal<br>
of optimization algorithm capable of perfectly solving all types<br>
of optimization problems. Because the characteristics and<br>
of optimization problems. Because the chara optimization aigorithm capable of perrectly solving all types<br>
algorithm orten leads to gas<br>
complexity of different problems vary significantly. With<br>
complexity of different problems vary significantly. With<br>
the rapid a or optimization problems. Because the characteristics and premature convergence<br>complexity of different problems vary significantly. With progresse, this interact<br>exponential growth in the volume of data generated across i complexity of different problems vary signincantly. With rapid and free complexity of different of technology has led to an exponential growth in the volume of data generated across impacting the algor various domains, acc the rapid advancement of technology has led to an<br>exponential growth in the volume of data generated across impacting<br>various domains, accompanied by increasing complexity proposes<br>and diversity of the data. However, chall ponential grown in the volume of data generated across<br>
impactung the algorithmic<br>
irolus diversity of the data. However, challenges such as data<br>
HGSO by creating a nee<br>
dundancy and excessively long modeling times have<br> various domains, accompanied by increasing complexity proposes tiree strategies to<br>and diversity of the data. However, challenges such as data recosion and the study of the data we gostion update formula, and<br>become signi and alwestiy of the data. However, challengs such as data<br>
redundancy and excessively long modeling times have<br>
become significant obstacles to effective data analysis. To<br>
mechanism for Lévy flig<br>
address these pressing redundancy and excessively long modeling times have<br>become significant obstacles the pressure of effective data analysis. To<br>mechanism for Lévy flights<br>increasing need for optimization algorithms that can handle<br>review of

become significant obstacles to effective data analysis. To<br>mechanism for Levy fight<br>address these pressing issues more efficiently, there is no increasing need for optimization algorithms that can handle<br>beth continuous a address these pressing issues more erriclently, there is an<br>increasing need for optimization algorithms that can handle<br>both continuous and discrete optimization problems HGSO algorithm along<br>simultaneously. The HGSO algor mereasure all or optimization algorithms in an analysis of the existing in the signal discrete optimization problems with manifestic products of this student in simultaneously. The HGSO algorithm is an attractive motivatio both continuous and discrete optimization problems<br>
simultaneously. The HGSO algorithm is an attractive motivation of this study. Section<br>
algorithm owing to the fact that equilibrium exploration and algorithm E HGSO secti simultaneously. The HOSO algorithm is an attractive motivation of this study. Section play pivotal role fact that equilibrium exploration and algorithm E\_HGSO. Section that makes HGSO suitable for solving complex optimiza algorium owing to the act that equilibrium exploration and<br>exploitation physical role in the algorith, a property<br>fund means that makes HGSO suitable for solving complex optimization<br>problems with many locally optimal solu explotation play protal role in the algoritm, a property<br>
that makes HGSO suitable for solving complex optimization<br>
problems with many locally optimal solutions.<br>
Henry's law is a fundamental principle of physical<br>
corro the method sum alternative behavior and compares them with more and the may locally optimal solutions.<br>
Henry's law is a fundamental principle of physical our modified algorithm to chemistry, proposed in 1803 during the st From the may locally optimal solutions.<br>
Henry's law is a fundamental principle of physical Section VI discusse<br>
chemistry, proposed in 1803 during the study of gas<br>
solubility in liquids. It can be expressed as: at consta The state of research is a munder of physical section VI discusses and conducted solubility in liquids. It can be expressed as: at constant II. BASIC PRINCIPLE OF 1 temperature and pressure, the solubility of a volatile so chemistry, proposed in 1805 during the study of gas<br>solubility in liquids. It can be expressed as: at constant<br>temperature and pressure, the solubility of a volatile solute<br>in a solution is proportional to the equilibrium solubiny in industs. It can be expressed as: at constant<br>
temperature and pressure, the solubility of a volatile solution in a solution is proportional to the equilibrium partial<br>
pressure of that solute above the liquid s Emperature and pressure, the solubility of a volatile solute<br>
in a solution is proportional to the equilibrium partial<br>
pressure of that solute above the liquid surface. The novel<br>
meta-heuristic algorithm for Henry's Gas all a solution is proportional to the equilibrium partial<br>
pressure of that solute above the liquid surface. The novel<br>
meta-heuristic algorithm for Henry's Gas Solubility In this section, the concept<br>
Optimization (HGSO) pressure of mat solute above the liquid surface. The novel<br>meta-heuristic algorithm for Henry's Gas Solubility<br>Depimization (HGSO) is inspired by the principles of Dytimization Algorithm<br>Henry's law, and it mimics the beha mean-neutristic algorithm for Ferry's Gas Solubility optimization Algorithm (HGSO) is inspired by the principles of Henry's law, and it mimics the behavior governed by this algorithm is inspired by the fundamental physical

Example 1<br>
Solution improves the speed of convergence, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. Fatma A. Hashim et al. Explorering provides the speed of convergence, solves real<br>engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>propo Figure 1.<br>
1. **Letters**<br>
1. The improves the speed of convergence, solves real<br>
1. engineering optimization problems, and obtains the optimal<br>
1. proposed an improved Henry's Gas Solubility optimization<br>
1. [35]<br>
1. propos **Exercise 15 Exercise 15 Exercise 15 Exercise 16 Exerc Exercise 1998**<br> **Exercise 1998**<br> **Exercise and the speed of convergence**, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. Fa (**Letters**<br>
which improves the speed of convergence, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. Fatma A. Hashim et al. [ **Example 19 Example 19 Example 10**<br>
which improves the speed of convergence, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. **Exercise 15 Exercise 15 Exercise 15 Exercise 15 Exercise 16 Exercise 16 Exercise models in mechanical design and manufacturing optimization problems. Fatma A. Hashim et al. [35] proposed an improved Henry's Gas Solubility Exercise 15 Exercise Solution**<br>
which improves the speed of convergence, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. Fat (**Letters**<br>
which improves the speed of convergence, solves real<br>
engineering optimization problems, and obtains the optimal<br>
variable in mechanical design and manufacturing<br>
optimization problems. Fatma A. Hashim et al. [ which improves the speed of convergence, solves real<br>engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>proposed an which improves the speed of convergence, solves real<br>engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>proposed an which improves the speed of convergence, solves real<br>engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>proposed an which improves the speed of convergence, solves real<br>engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization roblems. Fatma A. Hashim et al. [35]<br>proposed an engineering optimization problems, and obtains the optimal<br>variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>proposed an improved Henry's Gas Solubility optimization<br>(MHGSO) variable in mechanical design and manufacturing<br>optimization problems. Fatma A. Hashim et al. [35]<br>proposed an improved Henry's Gas Solubility optimization<br>(MHGSO) algorithm for the discovery of functional motifs<br>in DNA ge parameters by PAs and HGSO is get the escal portocol<br>pharmameter (MHGSO) algorithm for the discovery of functional motifs<br>(MHGSO) algorithm for the discovery of functional motifs<br>detecting the target modality. Serdar Ekinc proposed an improved Henry's Gas Solubility optimization<br>(MHGSO) algorithm for the discovery of functional motifs<br>in DNA genome sequences, which is capable of accurately<br>detecting the target modality. Serdar Ekinci et al. (MHGSO) algorithm for the discovery of functional motifs<br>in DNA genome sequences, which is capable of accurately<br>detecting the target modality. Serdar Ekinci et al. [36]<br>introduced a new the Henry's Gas Solubility Optimisa in DNA genome sequences, which is capable of accurately<br>detecting the target modality. Serdar Ekinci et al. [36]<br>introduced a new the Henry's Gas Solubility Optimisation<br>(OBL/HGSO) based on inverse learning. Cao et al. [37 detecting the target modality. Serdar Ekinci et al. [36]<br>introduced a new the Henry's Gas Solubility Optimisation<br>(OBL/HGSO) based on inverse learning. Cao et al. [37]<br>groposed a SVR-based prediction method, Henry<br>Solubili Introduced a new the Henry's Gas Solubility<br>(OBL/HGSO) based on inverse learning. C<br>proposed a SVR-based prediction method<br>Solubility optimization Algorithm, by randon<br>support vector regression machine parameter<br>range to f HBL/HGSO) based on inverse learning. Cao et al. [37]<br>oposed a SVR-based prediction method, Henry Gas<br>ububility optimization Algorithm, by randomly generating<br>propri vector regression machine parameters in a certain<br>oper to proposed a SVR-based prediction method, Henry Gas<br>Solubility optimization Algorithm, by randomly generating<br>support vector regression machine parameters in a certain<br>range to form a parameter population, the prediction<br>acc Solubility optimization Algorithm, by randomly generating<br>support vector regression machine parameters in a certain<br>range to form a parameter population, the prediction<br>accuracy (PA) to get the population and SVR used, and support vector regression macnine parameters in a certain<br>range to form a parameter population, the prediction<br>accuracy (PA) to get the population and SVR wased, and at<br>parameters by PAs and HGSO to get the best overall<br>pe

range to form a parameter population, the prediction<br>accuracy (PA) to get the population and SVR used, and at<br>the same time updating the population and the optimal SVR<br>parameters by PAs and HGSO to get the best overall<br>per accuracy (PA) to get the population and SVK used, and at<br>the same time updating the population and the optimal SVR<br>parameters by PAs and HGSO to get the best overall<br>performance. Davood Mohammadi et al. [38,39] borrowed a<br> the same time updating the population and the optimal SVR<br>parameters by PAs and HGSO to get the best overall<br>performance. Davood Mohammadi et al. [38,39] borrowed a<br>new scheme from quantum theory to update the position of<br> parameters by PAs and HGSO to get the best overall<br>performance. Davood Mohammadi et al. [38,39] borrowed a<br>new scheme from quantum theory to update the position of<br>each solution, improving the original algorithm to improve performance. Davood Mohammadi et al. [38,39] borrowed a<br>new scheme from quantum theory to update the position of<br>each solution, improving the original algorithm to improve<br>the exploration performance to explore the search new scheme from quantum theory to update the position of<br>each solution, improving the original algorithm to improve<br>the exploration performance to explore the search space,<br>named QHGSO.<br>HGSO algorithm exhibits a wide range each solution, improving the original algorithm to improve<br>the exploration performance to explore the search space,<br>named QHGSO.<br>HGSO algorithm exhibits a wide range of applications<br>across various fields; however, it still the exploration performance to explore the search space,<br>
HGSO algorithm exhibits a wide range of applications<br>
across various fields; however, it still encounters certain<br>
challenges including susceptibility to local opti named QHGSO.<br>
HGSO algorithm exhibits a wide range of applications<br>
across various fields; however, it still encounters certain<br>
challenges including susceptibility to local optima, and<br>
sluggish convergence speed. During HGSO algorithm exhibits a wide range of applications<br>across various fields; however, it still encounters certain<br>challenges including susceptibility to local optima, and<br>sluggish convergence speed. During the initial stage ross various rietas; nowever, it still encounters certain<br>allenges including susceptibility to local optima, and<br>alggish convergence speed. During the initial stage of<br>paper in the interaction among gases in the HGSO<br>gorit chailenges moluding susceptibility to local oplima, and<br>sluggish convergence speed. During the initial stage of<br>iteration, the interaction among gases in the HGSO<br>algorithm often leads to gas cluster agregation, resulting suggish convergence speed. During the mital stage of<br>iteration, the interaction among gases in the HGSO<br>algorithm often leads to gas cluster agregation, resulting in<br>promature convergence. However, as the iteration<br>progres nteration, the interaction among gases in the HGSO<br>algorithm often leads to gas cluster aggregation, resulting in<br>premature convergence. However, as the iteration<br>facilitating individuals to escape from local optima, there

algorithm often leads to gas cluster aggregation, resulting in<br>progresses, this interaction becomes less effective in<br>facilitating individuals to exape from local optima, thereby<br>facilitating individuals to exape form loca premature convergence. However, as the iteration<br>progresses, this interaction becomes less effective in<br>facilitating individuals to escape from local optima, thereby<br>impacting the algorithm's accuracy. Therefore, this pape progresses, this interaction becomes less errective in<br>facilitating individuals to escape from local optima, thereby<br>impacting the algorithm's accuracy. Therefore, this paper<br>proposes three strategies to address the shortc Tracturating individuals to escape from local optima, thereby<br>
impacting the algorithm's accuracy. Therefore, this paper<br>
proposes three strategies to address the shortcomings of<br>
HGSO by creating a new grouping search for mpacung the algorithm's accuracy. Interestore, this paper<br>proposes three strategies to address the shortcomings of<br>HGSO by creating a new grouping search formula, a new<br>position update formula, and the introduction of a gr Solony creating a new grouping search formula, a new<br>tion update formula, and the introduction of a grouping<br>hanism for Lévy flights.<br>Hence paper is structured as follows: Section I gives a<br>sew of the existing literature; sting literature; Section II describes the base<br>
um along with the shortcomings and<br>
is study. Section III presents the improved<br>
GSO and analyses the experimental results<br>
em with other algorithms. Section V applies<br>
lgor The paper is structured as follows: Section I givity<br>view of the existing literature; Section II describes the<br>GSO algorithm along with the shortcomings<br>otivation of this study. Section III presents the impr<br>gorithm E\_HGSO SISO algorithm along with the shortcomings and<br>activation of this study. Section III presents the improved<br>broton of this study. Section III presents the improved<br>gorithm E\_HGSO. Section IV gives the experimental<br>tup of th The<br>
Horizon anglem and the simulation of this study. Section III presents the improved<br>
algorithm E\_HGSO and analyses the experimental results<br>
and compares them with other algorithms. Section V applies<br>
our modified alg

meanware of the Henry's the experimental<br>algorithm E HGSO. Section IV gives the experimental results<br>and compares them with other algorithms. Section V applies<br>our modified algorithm to feature selection and finally,<br>Sect setup of the E\_HGSO and analyses the experimental results<br>and compares them with other algorithms. Section V applies<br>our modified algorithm to feature selection and finally,<br>Section VI discusses and concludes the study.<br>II and compares them with other algorithms. Section V applies<br>our modified algorithm to feature selection and finally,<br>Section VI discusses and concludes the study.<br>II. BASIC PRINCIPLE OF HENRY'S GAS SOLUBILITY<br>oPTIMIZATION A our modified algorithm to feature selection and finally,<br>Section VI discusses and concludes the study.<br>II. BASIC PRINCIPLE OF HENRY'S GAS SOLUBILITY<br>OPTIMIZATION ALGORITHM<br>A. Henry's law<br>In this section, the concept of the is a Henry's das Solubility<br>
H. BASIC PRINCIPLE OF HENRY'S GAS SOLUBILITY<br>
OPTIMIZATION ALGORITHM<br>
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In this section, the concept of the Henry's Gas Solubility<br>
stimization Algorithm (HGSO) will be introduced II. BASIC PRINCIPLE OF HENRY'S GAS SOLUBILITY<br>
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II. BASIC PRINCIPLE OF HENRY'S GAS SOLUBILITY<br>
OPTIMIZATION ALGORITHM<br> *A. Henry's law*<br>
In this section, the concept of the Henry's Gas Solubility<br>
Optimization Algorithm (HGSO) will be introduced. The<br>
algorithm is inspi OPTIMIZATION ALGORTHIM<br> *A. Henry's law*<br>
In this section, the concept of the Henry's Gas Solubility<br>
Optimization Algorithm (HGSO) will be introduced. The<br>
algorithm is inspired by the famous Henry's law. Simulating<br>
the A. Henry's law<br>In this section, the concept of the Henry's Gas Solubility<br>Optimization Algorithm (HGSO) will be introduced. The<br>algorithm is inspired by the famous Henry's law. Simulating<br>the cumulative behaviour of natura In this section, the concept of the Henry's Gas Solubility<br>Optimization Algorithm (HGSO) will be introduced. The<br>algorithm is inspired by the famous Henry's law. Simulating<br>the cumulative behaviour of natural gas, the HGSO relationship:

$$
S_g = H \times P_g \tag{1}
$$

**i g**  $S_g = H \times P_g$  (1) equilibrium from other gases of the same ty<br>then ranked to find the best gas in the entired stand and  $P_g$  is the partial pressure of **a i ly duating of Henry's coefficient: The I are updated Engineering Letters**<br>  $S_g = H \times P_g$  (1) equilibrium from other gases of<br>
Where *H* is Henry's constant and  $P_g$  is the partial pressure of<br>
the gas. *H* gives a good indication of the amount of gas<br>
dissolved, strictly spea **Engineering Letters**<br>  $S_g = H \times P_g$  (1) equilibrium from other gases of<br>
where *H* is Henry's constant and  $P_g$  is the partial pressure of<br>
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Where *H* is Henry's constant and  $P_g$  is the partial pressure of<br>
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here *H* is Henry's constant and  $P_g$  is the partial pressure of<br>  $\epsilon$  gas. *H* gives a good indication of the amount of gas<br>
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then ranked to find the best<br>
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the gas. H gives a good indication of the amount of gas<br>
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then ranked to find the best gas<br>
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approximate l  $S_g = H \times P_g$  (1) equilibrium then ranked the gas. *H* gives a good indication of the amount of gas dissolved, strictly speaking, Henry's law is only an approximate law and cannot be applied to systems with higher pressures. **Engineering Letters**<br>  $S_g = H \times P_g$  (1) equilibrium from other gases of the s<br>
then ranked to find the best gas in the<br>
updating of Henry's coefficient:<br>
(ood indication of the amount of gas<br>
greaking. Henry's law is only a **Engineering Letters**<br>  $S_g = H \times P_g$  (1) equilibrium from other gases of the ranked to find the best gas in<br>
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then ranked to find the best gas in the entire<br>
constant and  $P_g$  is the partial pressure of<br>
are updated applying the following equatio **Engineering Letters**<br>  $S_g = H \times P_g$  (1) equilibrium from other gases of the same type. The then ranked to find the best gas in the entire group<br>
y's constant and  $P_g$  is the partial pressure of **the same updated applying th**  $S_g = H \times P_g$  (1) equilibrium from other gases of the same type. The gases in the center of gases in the cent

$$
\frac{d \ln H}{d(1/T)} = \frac{-\nabla_{sol}E}{R}
$$
 (2) follow

$$
H(T) = \exp(B/T) \times A \tag{3}
$$

a function of temperature and has orbing to do with<br>
The Henry's coefficient varies with temperature, and as<br>
the temperature increases, the volatility of the volatile solute of the enthalpy's coefficient increases, which **PRESSURE ART INTERT AND THE GAS CONSTRANT CONTROLLED THE GAS CONSTRANT IN THE GAS CONSTRANT IN THE GAS CONSTRANT AND ARE SCHOOLS THE GAS CONSTRANT AND A BASE CONSTRANT AND A BASE CONSTRANT AND <b>A** and *H* and *H* are the The Henry's coefficient varies with temperature, and as<br>the temperature increases, the volatility of the volatile solute<br>increases and the Henry's coefficient increases, which can be<br>described by the van't Hoff equation a increases and the Henry's coefficient increases, which can be<br>
described by the van't Hoff equation as follows:<br>  $\frac{d \ln H}{d(1/T)} = \frac{-\nabla_{sol}E}{R}$  (2)<br>  $H(T) = \exp(B/T) \times A$  (3)<br>
Where  $\nabla_{sol}E$  is the enthalpy of dissolution, the *B.*  $H(T) = \exp(B/T) \times A$  (3)<br>
here  $\nabla_{sol}E$  is the enthalpy of dissolution, the gas constant wis the gas constant, and *A* and *B* are the two parameters of p relationship between *H* and *T*. *H* is a function of is rameters

$$
H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}
$$
 (4)

 $H(I) = \exp(B/I) \times A$  (3)<br>
here  $\nabla_{so}E$  is the enthalpy of dissolution, the gas constant<br>
is the gas constant, and A and B are the two parameters of partial pressure of the g<br>
e relationship between H and T. H is a function of Where  $\nabla_{sol}E$  is the enthalpy of dissolution, the gas constant<br> *R* is the gas constant, and *A* and *B* are the two parameters of partial pressure of the g<br>
the relationship between *H* and *T*. *H* is a function of is Where  $\nabla_{sol}E$  is the enthalpy of dissolution, the gas constant<br> *R* is the gas constant, and *A* and *B* are the two parameters of<br>
parameters of<br>
the relationship between *H* and *T*. *H* is a constant is is a constant R is the gas constant, and A and B are the two parameters of<br>
the relationship between H and T. H is a function of<br>
parameters A and B.<br>
Position update: The valuation is valid when  $\nabla_{sol}E$  is a constants:<br>  $H(T) = \exp(-C \times ($ the relationship between *H* and *T*. *H* is a function of<br>parameters *A* and *B*.<br>**Position update:** The way in<br>cluster gas is updated:<br> $H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}$  (4)<br> $K_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \alpha \times (S_i$ <br>*HGSO mathemati* parameters A and B.<br> **Position update:** The way<br>
van's Hoff equation is valid when  $\nabla_{sol}E$  is a constants:<br>  $H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}$  (4)<br>  $\int_{F \times r \times \alpha} f(F) + F \times r \times \alpha$ <br>
B. HGSO mathematical model<br>
HGSO is characteriz Van's Hoff equation is valid when  $\nabla_{so}E$  is a constants:<br>  $H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}$  (4)<br>  $\frac{X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \alpha \times (S^2)}{+F \times r \times \alpha \times (S^2)}$ <br>
B. HGSO is characterized by several fundamental structural<br>
compone  $H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}$  (4)  $K_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \alpha$ <br>  $B$ . HGSO mathematical model<br>
HGSO is characterized by several fundamental structural<br>
components, including the initialization of candidate<br>
solutions, the  $H(T) = \exp(-C \times (1/T - 1/T^{\theta})) \times H^{\theta}$  (4)<br>
B. HGSO mathematical model<br>
HGSO is characterized by several fundamental structural<br>
components, including the initialization of candidate<br>
solutions, the iterative refinement of those  $H(Y) = \exp(-C \times (1/T - 1/T)) \times H$  (4)<br>  $+F \times r \times a \times (5/T)$ <br>
HGSO is characterized by several fundamental structural<br>
mponents, including the initialization of candidate<br>
alutions, the terrative refinement of those solutions, the aluti B. HGSO mathematical model<br>
HGSO is characterized by several fundamental structural<br>
components, including the initialization of candidate<br>
solutions, the iterative refinement of those solutions, the In Eq<br>
evaluation of *B. HGSO mathematical model*  $\gamma = \beta \times e$ <br>
HGSO is characterized by several fundamental structural<br>
mponents, including the initialization of candidate<br>
lutions, the iterative refinement of those solutions, the In Eqs. 10 a For the interactions with *N* gas particles is initialized with the culture of the pole of the pole of the solutions, the interactions of candidate solutions, the iterative refinement of those solutions, the *i*n Eqs. 10 rich is including the initialization of candidate<br>
components, including the initialization of candidate<br>
solutions, the iterative refinement of those solutions, the In Eqs. 10 and 11,  $X_{i,j}$ <br>
evaluation of their fitness components, including the initialization of candidate<br>
solutions, the iterative refinement of those solutions, the<br>
solution of their fitness, and the selection of the optimal<br>
solution. It maintains a population of candi

solutions, the iterative remement of those solutions, the in Eqs. 10 and 11,  $X_{(i,j)}$  is u<br>
solution. It maintains a population of candidate solutions in<br>
solution. It maintains a population of candidate solutions in<br>
the **Example 10** is a mumber of the Figure of the Figure of the The cluster *j*, *r* is a ranoom number of interaction of the form of gas particles dissolved in a given liquid. The cluster *j*, and  $X_{best}$  is the best propert solution. It infiniting a population of cannot expectively, and the component phase stations in a given liquid. The propulation, we<br>approperties of these gas particles dissolved in a given liquid. The population, we<br>repro **Example 1.1** The *X*(*i*) denotes the interaction of candidate in the whole population, resolutions with *N* gas particles is initialised with the used to guide the direction or relationship between the number of gases a **Note that the set is a random** in the window of the gases that the window is a random number of gases *i*, the value of the gases, as well as the number of gases *i*, the value of the problem of falling into a local in t Example the positions where  $\chi_{ij}$  and  $\chi_{mkl}$  is the positions of the gases, as well as the number of gases and the positions **Escape from local op** of the gases, as well as the number of gases *i*, the value of proble

$$
X_i(t+1) = X_{\min} + r \cdot (X_{\max} - X_{\min})
$$
 (5)

$$
H_j(t) = l_1 \times rand(0,1), P_{i,j} = l_2 \times rand(0,1), C_j = l_3 \times rand(0,1)
$$
 (6)

For the gases, as well as the number of gases *i*, the value of the gases, as well as the number of gases *i*, the value of the best<br>in the cluster *j*, and the value of the  $\nabla_{so}E/R$  constant  $j(C_i)$ , worst a<sub>i</sub> respecti Example 1. The proposition of the same of the same value of the same the same of the solution of Henry's constant  $j(H(t))$ , the partial pressure  $P_{i,j}$  of the gas in the b the b in the cluster *j*, and the value of the  $\nab$ 

Aggregation and evaluation: The population agent is<br>  $\begin{array}{ll}\n\text{MSE} & \text{MSE} \\
\text{MSE} & \text{MSE} \\
\text{MSE$ divided into an evidation: The population agent is<br>
divided into an equal number of clusters based on the type of<br>  $H_j(t) = l_1 \times rand(0,1), P_{i,j} = l_2 \times rand(0,1), C_j = l_3 \times rand(0,1)$  (5)<br>
Where N is the population size<br>
where  $X_{(i)}$  denot  $K_i(t+1) = X_{min} + r \cdot (X_{max} - X_{min})$ <br>  $H_j(t) = I_i \times rand(0,1), P_{i,j} = I_2 \times rand(0,1), C_j = I_3 \times rand(0,1)$  (5)<br>
Where *N* is the population<br>
where  $X_{(i)}$  denotes the position of the *i*th gas among all gases<br>
Where *N* is the population<br>
where  $X_{(i$  $X_i(t+1) = X_{min} + r \cdot (X_{max} - X_{min})$  (5)<br>  $H_j(t) = l_1 \times rand(0,1), P_{i,j} = l_2 \times rand(0,1), C_j = l_3 \times rand(0,1)$  (6) Where *N* is the population<br>
Where  $X_{(i)}$  denotes the position of the *i*th gas among all gases<br>
Where  $X_{(i)}$  is a random number bet  $X_i(t+1) = X_{min} + r \cdot (X_{max} - X_{min})$  (5)<br>  $H_j(t) = l_1 \times rand(0,1), P_{i,j} = l_2 \times rand(0,1), C_j = l_3 \times rand(0,1)$  (6) Where *N* is the population<br>
where  $X_{(i)}$  denotes the position of the *i*th gas among all gases<br>
where  $X_{(i)}$  denotes the position o

Explicit Content of the same type. The gases are<br>equilibrium from other gases of the same type. The gases are<br>then ranked to find the best gas in the entire group.<br>Updating of Henry's coefficient: The Henry coefficients<br>ar then ranked to find the best gas of the same type. The gases are<br>then ranked to find the best gas in the entire group.<br>**Updating of Henry's coefficient:** The Henry coefficients<br>are updated applying the following equation: **Letters**<br> **Updating of Henry's coefficient:** The gases are<br> **Updating of Henry's coefficient:** The Henry coefficients<br> **Updating of Henry's coefficient:** The Henry coefficients<br>  $H_i(t+1) = H_i(t) \times \exp(-C_i \times (\frac{1}{\pi(s)} - \frac{1}{\pi(t)})$ 

Letters
equilibrium from other gases of the same type. The gases are then ranked to find the best gas in the entire group.
Updating of Henry's coefficient: The Henry coefficients are updated applying the following equation:
$H_j(t+1) = H_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$
$T(t) = \exp(-t / iter)$
Where $H_j$ is the Henry's coefficient of the <i>j</i> th cluster, <i>T</i> is the temperature, $T^{\theta}$ is a constant with a constant value of 289.15 and <i>iter</i> is the maximum number of iterations.
Solubility update: At the <i>t</i> th iteration, the solubility of the <i>i</i> th gas particle in the <i>j</i> th cluster is updated using the following equation:

$$
I'(t) = \exp(-t / iter)
$$
 (8)

temperature,  $T^{\theta}$  is a constant with a const

the *i*th gas particle in the *j*th cluster is updated using the following equation: other gases of the same type. The gases are<br>
d the best gas in the entire group.<br> **EVALUATE:** The Henry coefficients<br>
ing the following equation:<br>  $T_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7)<br>  $T(t) = \exp(-t / iter)$  (8)<br>
[enry's coeffi equilibrium from other gases of the same type. The gases are<br>then ranked to find the best gas in the entire group.<br> **Updating of Henry's coefficient:** The Henry coefficients<br>
are updated applying the following equation:<br> **Solubility update:** At the *tale syperation* of  $H_j(t+1) = H_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7)<br>  $H_j(t+1) = H_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7)<br>  $T(t) = \exp(-t / iter)$  (8)<br>
there  $H_j$  is the Henry's coefficient of the *j*th cluste the *<sup>i</sup>*th gas particle in the *<sup>j</sup>*th cluster is updated using the Following equation:<br>  $H_j(t+1) = H_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T(t)}))$ <br>  $T(t) = \exp(-t / iter)$ <br>
Where  $H_j$  is the Henry's coefficient of the *j*th clust<br>
temperature,  $T^{\theta}$  is a constant with a constant valu<br>
and *iter* is the maximum nu the following equation:<br>  $t$   $\times$   $\times$   $\times$   $p(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7)<br>  $t$ ) =  $\exp(-t / iter)$  (8)<br>  $t$ 's coefficient of the *j*th cluster, *T* is the<br>
onstant with a constant value of 289.15<br>
um number of iterations.<br>  $:$ ther gases of the same type. The gases are<br>the best gas in the entire group.<br>**ii** *i* **j s coefficient:** The Henry coefficients<br>g the following equation:<br> $(i) \times \exp(-C_j \times (\frac{1}{T(i)} - \frac{1}{T^{\theta}}))$  (7)<br> $(i) = \exp(-t / iter)$  (8)<br>ary's co  $T(t) = \exp(-t / iter)$  (8)<br>
Where *H<sub>j</sub>* is the Henry's coefficient of the *j*th cluster, *T* is the<br>
temperature, *T*<sup>*i*</sup> is a constant with a constant value of 289.15<br>
solubility **update**: At the *t*th iteration, the solubility *I* (*t*) = exp( $-i$  *l ter*) (8)<br>
Where *H<sub>j</sub>* is the Henry's coefficient of the *j*th cluster, *T* is the<br>
temperature, *T*<sup>*g*</sup> is a constant with a constant value of 289.15<br>
and *iter* is the maximum number of iterat Where  $H_j$  is the Henry's coefficient of the *j*th cluster<br>temperature,  $T^{\theta}$  is a constant with a constant value o<br>and *iter* is the maximum number of iterations.<br>**Solubility update:** At the *t*th iteration, the solu<br>t here *H<sub>j</sub>* is the Henry's coefficient of the *j*th cluster, *T* is the<br>mperature, *T<sup>0</sup>* is a constant with a constant value of 289.15<br>d *iter* is the maximum number of iterations.<br>**Solubility update:** At the *t*th itera temperature,  $T^{\theta}$  is a constant with a constant value of 289.15<br>and *iter* is the maximum number of iterations.<br>**Solubility update:** At the *t*th iteration, the solubility of<br>the *i*th gas particle in the *j*th cluster

$$
S_{i,j}^t = K \times H_j^{t+1} \times P_{i,j}^t \tag{9}
$$

\n The 
$$
0
$$
 is a  $0$  and  $0$  and  $0$  is a  $0$  and  $0$ .\n

\n\n The  $H_j(t+1) = H_j(t) \times \exp(-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7) and  $0$  (8) are the  $H_j$  is the Henry's coefficient of the  $j$ th cluster,  $T$  is the  $H_j$  is a constant with a constant value of 289.15, and  $0$  is  $0$  is the maximum number of iterations.\n

\n\n Solubility update: At the  $t$ th iteration, the solubility of  $t$  in the  $t$ th cluster is updated using the  $0$  is a particle in the  $j$ th cluster is updated using the  $S_{i,j} = K \times H_j^{t+1} \times P_{i,j}^t$  (9) have  $S_{i,j} = K \times H_j^{t+1} \times P_{i,j}^t$  (9) have  $S_{i,j} = K \times H_j^{t+1} \times P_{i,j}^t$  (9) have  $S_{i,j} = K \times H_j^{t+1} \times P_{i,j}^t$  (10) have a constant, the  $0$  is a constant

min max min ( 1) ( ) *X t X r X X <sup>i</sup>* (5) <sup>1</sup> , 2 <sup>3</sup> ( ) (0,1), (0,1), (0,1) *H t l rand P l rand C l rand <sup>j</sup> i j <sup>j</sup>* (6)  $\frac{1}{f} \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}}))$  (7)<br> *(iter)* (8)<br> *(iter)* (8)<br>
to f the *j*th cluster, *T* is the<br>
a constant value of 289.15<br>
fi iterations.<br>
iteration, the solubility of<br>
ster is updated using the<br>  $\lim_{t \to \infty} P_{i,j}^t$  $-C_j \times (\frac{1}{T(t)} - \frac{1}{T^{\theta}})$  (7)<br>  $(-t / iter)$  (8)<br>
Sient of the *j*th cluster, *T* is the<br>
tih a constant value of 289.15<br>
fer of iterations.<br>
cluster is updated using the<br>  $H_j^{t+1} \times P_{i,j}^t$  (9)<br>
bility of the gas,  $P_{i,j}$  is partial pressure of the gas in the *j*th cluster of the gas, and *K*<br>
is a constant therein.<br> **Position update:** The way in which the position of the *j*th<br>
cluster gas is updated:<br>  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t)$ is a constant therein.<br> **Position update:** The way in which the position of the *j*th<br>
cluster gas is updated:<br>  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t) - X_{i,j}(t))$  (10)<br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{$ **Position update:** The way in which the position of the *j*th<br>
cluster gas is updated:<br>  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t) - X_{i,j}(t))$  (10)<br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon})$ cluster gas is updated:<br>  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t) - X_{i,j}(t))$  (10)<br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon})$ ,  $\varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to deno  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t) - X_{i,j}(t))$ <br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon}), \varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cl  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,best}(t) - X_{i,j}(t))$ <br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon}), \varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cl  $+F \times r \times \alpha \times (S_{i,j}(t) \times X_{best}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon})$ ,  $\varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cluster *j*, *r* is a random number, *t* represen  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon})$ ,  $\varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cluster *j*, *r* is a random number, *t* represents the current<br>
number of iterations,  $\gamma = \beta \times \exp(-\frac{F_{best}(t) + \varepsilon}{F_{i,j}(t) + \varepsilon})$ ,  $\varepsilon = 0.05$  (11)<br>In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br>*i* in cluster *j*, *r* is a random number, *t* represents the current<br>number of iterations,  $X_{$  $y = p \times \exp(-\frac{p}{F_{i,j}}(t) + \varepsilon), \varepsilon = 0.05$  (11)<br>
In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cluster *j*, *r* is a random number, *t* represents the current<br>
number of iterations,  $X_{(i,best)}$  is t In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br>n cluster *j*, *r* is a random number, *t* represents the current<br>mber of iterations,  $X(i_{i,bes})$  is the best position of gas *i* in<br>uster *j*, and  $X_{best}$  is In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br> *i* in cluster *j*, *r* is a random number, *t* represents the current<br>
number of iterations,  $X_{(i,bex)}$  is the best position of gas *i* in<br>
cluster *j*, a in Eqs. 10 and 11,  $X(i_0)$  is used to denote the position of gas<br> *i* in cluster *j*, *r* is a random number, *t* represents the current<br>
number of iterations,  $X(i_0k_{\text{est}})$  is the best position of gas *i* in<br>
cluster *j t* in cluster *j*, *r* is a random number, *t* represents the current number of iterations,  $X(i, b_{est})$  is the best position of gas *i* in cluster *j*, and  $X_{best}$  is the best position of gas *i* in the whole population, w s a constant therem.<br> **Position update:** The way in which the position of the *j*th<br>
Luster gas is updated:<br>  $X_{i,j}(t+1) = X_{i,j}(t) + F \times r \times \gamma \times (X_{i,bin}(t) - X_{i,j}(t))$  (10)<br>  $+ F \times r \times \alpha \times (S_{i,j}(t) \times X_{i,bin}(t) - X_{i,j}(t))$ <br>  $\gamma = \beta \times \exp(-\frac{F_{best$ gases in cluster *i*, *a* denotes the effect of other gas particles<br>on the *i*th particle, and  $\beta$  is a constant.  $F_{(i,j)}$  and  $F_{best}$  denote<br>the fitness of gas *i* in cluster *j* and the fitness of the best gas<br>in the wh In Eqs. 10 and 11,  $X_{(i,j)}$  is used to denote the position of gas<br>cluster *j*, *r* is a random number, *r* represents the current<br>ther of iterations,  $X_{(b, bce)}$  is the best position of gas *i* in<br>teter *j*, and  $X_{bext}$  is

on the *i*th particle, and  $\beta$  is a constant.  $F_{(i,j)}$  and  $F_{best}$  denote<br>the fitness of gas *i* in cluster *j* and the fitness of the best gas<br>in the whole population, respectively, and the value of *F* is<br>used to guide the whole population, respectively, and the value of *F* is<br>ed to guide the direction of gas movement.<br>**Escape from local optimum:** In order to solve the<br>oblem of falling into a local optimum during the search for<br>best ga used to guide the direction of gas movement.<br> **Escape from local optimum:** In order to solve the problem of falling into a local optimum during the search fo<br>
the best gas, the HSGO algorithm uses Eq. 12 to update the wor

$$
Nw = N \times (rand(c_2 - c_1) + c_1), c_1 = 0.1, c_2 = 0.2 \quad (12)
$$

respectively.

$$
G_{(i,j)} = G_{\min(i,j)} + r \times (G_{\max(i,j)} - G_{\min(i,j)}) \tag{13}
$$

*Nw* = *N* × (*rand*( $c_2 - c_1$ ) +  $c_1$ ),  $c_1 = 0.1$ ,  $c_2 = 0.2$  (12)<br>Where *N* is the population size, *rand* is a random number<br>between [0, 1],  $c_1$ ,  $c_2$  are constants with values 0.1, 0.2<br>respectively.<br>**Update the p** *Nw* = *N* × (*rand*( $c_2 - c_1$ ) +  $c_1$ ),  $c_1$  = 0.1,  $c_2$  = 0.2 (12)<br>Where *N* is the population size, *rand* is a random number<br>between [0, 1], *ct*, *c*<sub>2</sub> are constants with values 0.1, 0.2<br>respectively.<br>Update th Where *N* is the population size, *rand* is a random number<br>between [0, 1], *c<sub>1</sub>*, *c<sub>2</sub>* are constants with values 0.1, 0.2<br>respectively.<br>**Update the position of the worst individual:** Position<br>update for the worst agen

**Engineering Letters**<br>III. THE PROPOSED E\_HGSO ALGORITHM<br>pasic HGSO has the disadvantages of slowly<br>ence and falling into local optimal solutions. In<br>solve this drawback, this paper carries out three If the gas *i* satisfi **Engineering Letters**<br>III. THE PROPOSED E\_HGSO ALGORITHM<br>The basic HGSO has the disadvantages of slowly<br>nvergence and falling into local optimal solutions. In<br>der to solve this drawback, this paper carries out three<br>provem **Engineering Letters**<br>
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convergence and falling into local optimal solutions. In<br>
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order to solve this drawback, this paper carries out thre III. THE PROPOSED E\_HGSO ALGO<br>The basic HGSO has the disadvantag<br>convergence and falling into local optima<br>order to solve this drawback, this paper ca<br>improvements on the basis of the original alg<br>are as follows:<br>A. Creati **Engineering Lette**<br>
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The basic HGSO has the disadvantages of slowly<br>
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convergence and falling into local optimal solutions. In<br>
order to solve this drawback, this paper carries out three<br>
intra-group search III. THE PROPOSED E\_HGSO ALGORITHM<br>
The basic HGSO has the disadvantages of slowly<br>
convergence and falling into local optimal solutions. In<br>
order to solve this drawback, this paper carries out three<br>
improvements on the The basic HGSO has the disadvantages of slowly<br>convergence and falling into local optimal solutions. In<br>order to solve this drawback, this paper carries out three<br>improvements on the basis of the original algorithm, which The basic HGSO has the disadvantages of slowly<br>convergence and falling into local optimal solutions. In<br>order to solve this drawback, this paper carries out three<br>improvements on the basis of the original algorithm, whic **Engineering Letters**<br>
copose E\_HGSO ALGORITHM<br>
O has the disadvantages of slowly<br>
dling into local optimal solutions. In<br>
drawback, this paper carries out three<br>
the gas *i* satisfies Ex<br>
be basis of the original algorit

*r* (14)

$$
r < \mu e^{-\frac{t}{T_{\text{max}}}} \tag{15}
$$

**Engineering Letters**<br>
stab E\_HGSO ALGORITHM<br>
as the disadvantages of slowly<br>
into local optimal solutions. In<br>
base, this paper carries out three<br>
intra-group scarch will be performed, otherwise, this paper carries out t *r* <  $\mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>
8. 14 and 15 at the same time, the<br>
be performed, otherwise the<br>
carried out, in which  $\lambda$  and  $\mu$  are<br>
et manually. *tan*h is a hyperbolic<br>
s characterised by the fact that it<br>
brigin, w **Example 18 and**  $r < \mu e^{-\frac{t}{T_{\text{max}}}}$  **(15)**<br>If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>tra-group search will be performed, otherwise the<br>ter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br> intered in the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are constants that need to be set ma **i**<br> **i**  $r < \mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>
If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>
intra-group search will be performed, otherwise the<br>
inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br> **constants that need to be set manually.** *tan* **constants that need to be set manually.** *tan***h** is a hyperbolic that is a hyperbolic that is a hyperbolic that is a hyperbolic that need to be set manually. *tan***h** is a the sum of the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be performed, otherwise the inter-group search will be carried out, in whic the value of  $r < \mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>
If the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are  $r < \mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>intra-group search will be performed, otherwise the<br>inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br>constants tha *F* <  $\mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>ra-group search will be performed, otherwise the<br>ter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br>nstants that n  $r < \mu e^{-\frac{t}{T_{\text{max}}}}$  (15)<br>If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>ra-group search will be performed, otherwise the<br>energroup search will be carried out, in which  $\lambda$  and  $\mu$  are<br>nstants that need  $r < \mu e^{-T_{\text{max}}}$  (15)<br>
If the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>
intra-group search will be errformed, otherwise the<br>
inter-group search will be carried out, in which *i* a rad  $\mu$  are<br>
constants that If the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are constants that need to be set manually. If the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are constants that need to be set manually. If the gas *i* satisfies Eqs. 14 and 15 at the same time, the intra-group search will be performed, otherwise the inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are constants that need to be set manually. **Engineering Letters**<br>
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in the set of the gas *i* satisfies Eqs. 14 and 15 at the same time, the<br>
rerise out three group search will be performed, otherwis **EXERCUAS (** 1)  $r < \mu e^{-\frac{t}{Im\omega}}$  (15)<br>
SO has the disultantiages of slowly  $r < \mu e^{-\frac{t}{Im\omega}}$  (15)<br>
fielling into local optimal solutions i. If the gas *i* satisfies Eqs. 14 and 15 at the same time, the distance local opt **Example 2.1 Example 2.1 The Example 2.1 The CONDITER CONDITED** (15) falling into total optimal solutions. In<br>
its drawback, this paper curries out lotting 2.1 **The gas** *i* satisfies Figs. 14 and 15 at the same tim **Engineering Letters**<br>
In the same interesting the same time, the souties of the same time, the souties of the same inter-group search will be performed, one-wise the inter-group search will be performed, one-wise the int **Engineering Letters**<br>
SEED FI\_HGSO AT GORTITIM<br>
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IDENTIFY (15)<br>
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two stochastic gases, adding diversity and randomness to the search, as shown in equation (16). intra-group search will be performed, otherwise the<br>inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br>constants that need to be set manually. *tan*h is a hyperbolic<br>tangent function, which is characterise inter-group search will be carried out, in which  $\lambda$  and  $\mu$  are<br>constants that need to be set manually. *tan*h is a hyperbolic<br>tangent function, which is characterised by the fact that it<br>takes the value of 0 at the or while speeding up convergence, also leads to a rapid loss of<br>population diversity in the algorithm, and the algorithm<br>tends to fall into a local optimum. For this disadvantage, this<br>paper designs a new prey encircling for

However, the electricity of the work at the same time, to avoid  
\nthe local optimal. Meanwhile, we introduce the search factor  
\n*α, β,* to improve the accuracy:

\nThen, while speeding up convergence, also leads to a rapid loss of  
\npopulation diversity in the algorithm, and the algorithm  
\ntends to fall into a local optimum. For this disadvantage, this  
\n
$$
r < -\tanh(\lambda \times \frac{T_{\text{max}} - t}{T_{\text{max}}})
$$
\n(14)

\nThere are the unequal random numbers.

\nWhere *rr*<sub>1</sub>, *rr*<sub>2</sub> are three unequal random numbers.

\nC. *New formula for updating the worst gas*

\nC. *New formula for updating the worst gas*

\nThe position renewal process in the HGSO algorithm tends to fall into a local optimum. For this disadvantage, this paper designs a new prey encircling formula that introduces two stochastic gases, adding diversity and randomness to the search, as shown in equation (16).

\nWhere *rr*<sub>1</sub>, *rr*<sub>2</sub> are three unequal random numbers.

\nC. *New formula for updating the worst gas*

\nThe position renewal process in the HGSO algorithm is charged. In performing the sensitivity analysis, we select  
\nanallysed. In performing the sensitivity analysis, we select  
\nthe algorithm several times with different  
\nthe algorithm several times with different

*B*, to improve the accuracy:<br>  $r < -\tanh(\lambda \times \frac{T_{\text{max}} - t}{T_{\text{max}}})$  (14) paper designs a two stochastic gase at two stochastic gases at two stochastic gases at two stochastic gas search, as shown<br>  $X_{i,j}(t+1) = X_{rr1}(t) + \left[\left(\frac{T_{\$  $r < -\tanh(\lambda \times \frac{T_{\text{max}} - t}{T_{\text{max}}})$  (14) paper designs a new prey encire<br>
two stochastic gases, adding div<br>
search, as shown in equation (1<br>  $X_{i,j}(t+1) = X_{r1}(t) + [(\frac{T_{\text{max}} - 0.5t}{T_{\text{max}}})^2 \cos(2\pi r) \gamma \times X_{best}(t) - (1 + S_{i,j}(t))]$ <br>
here  $r < -\tanh(\lambda \times \frac{T_{\text{max}} - t}{T_{\text{max}}})$  (14) paper designs a new prey encontrol to the different transition of the state of the shown in equation of the state patt  $X_{i,j}(t+1) = X_{r+1}(t) + \left[\frac{T_{\text{max}}}{T_{\text{max}}}\right]^2 \cos(2\pi r) \gamma \times X_{best}(t) - (1 + S_{i,j}(t))$ <br>
Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. *New formula for updating the worst gas*<br>
the sensitivity of these two analysed. In perfo search, as shown in equat<br>
search, as shown in equat<br>  $X_{i,j}(t+1) = X_{r1}(t) + \left[\frac{T_{\text{max}} - 0.5t}{T_{\text{max}}}\right]^2 \cos\left(2\pi r\right) \gamma \times X_{best}(t) - (1 + \frac{1}{2})^2 \cos\left(2\pi r\right) \gamma \times X_{best}(t) - (1 + \frac{1}{2})^2 \cos\left(2\pi r\right) \gamma \times X_{best}(t) - (1 + \frac{1}{2})^2 \cos\left(2\pi r\right) \gamma$  $X_{i,j}(t+1) = X_{r,1}(t) + \left[\left(\frac{T_{\text{max}} - 0.5t}{T_{\text{max}}}\right)^2 \cos\left(2\pi r\right) \gamma \times X_{best}(t) - (1 + S_{i,j})\right]$ <br>
Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. *New formula for updating the worst gas*<br>
The search pattern of the HGSO alg  $X_{i,j}(t+1) = X_{r1}(t) + \left[ \left( \frac{T_{\text{max}} - 0.5t}{T_{\text{max}}} \right)^2 \cos(2\pi r) \gamma \times X_{\text{best}}(t) - (1 + T_{\text{max}})$ <br>
Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. *New formula for updating the worst gas* analysed. In performing<br>
The sear  $X_{i,j}(t+1) = X_{r+1}(t) + \left[ \left( \frac{T_{\text{max}} - 0.5t}{T_{\text{max}}}\right)^2 \cos\left(2\pi r\right) \gamma \times X_{best}(t) - (1 + S_{i.}) \right]$ <br>
Where *rr*<sub>1</sub>, *rr*<sub>2</sub> are three unequal random numbers.<br>
C. *New formula for updating the worst gas* the sensitivity of these two  $A_{i,j}(t+1) = A_{r1}(t) + [(1 - \frac{1}{T_{\text{max}}}) \cos(\frac{2\pi r}{\gamma}) \times A_{best}(t) - (1 + A_{i}) \cos(\frac{2\pi r}{\gamma})]$ <br>
Where *rr*, *rr* are three unequal random numbers.<br>
C. *New formula for updating the worst gas* the sensitivity of these to analysed. In per Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. New formula for updating the worst gas<br>
the sensitivity of these<br>
convergent pattern of the HGSO algorithm is<br>
different types of functionarctized by its simplicity Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. New formula for updating the worst gas<br>
the sensitivity of these tanget direct and yead. In performing the<br>
towards the target during each search. However, this dif Where  $rr_1$ ,  $rr_2$  are three unequal random numbers.<br>
C. New formula for updating the worst gas<br>
The search pattern of the HGSO algorithm is<br>
different types of functions the search pattern of the HGSO algorithm is<br>
diffe algorithm.  $r < - \tanh(\lambda \frac{T_{\text{rms}} - t}{T_{\text{max}}})$ <br>
(14) peach design into a local optimization, therefore, the space of the thereby diminishing its local search capability. To tackle this<br>
challenge, we have introduced a novel formula for updating<br>
the position of the worst gas agent and incorporated the Lévy<br>
from Fig. 1, it can be s<br>
flight challengie, we have introduced a novel formula for updating<br>
flight mechanism. By updating the position of the worst<br>
flight mechanism. By updating the position of the worst<br>
agent, the algorithm can converge more rapidly the position of the worst gas agent and incorpor<br>flight mechanism. By updating the position<br>agent, the algorithm can converge more rap<br>better solutions. This optimization not only<br>time but also improves the overall effici Experience in an experiment of the difference of E HGSO and<br>
Better solutions. This optimization not only saves search<br>
time but also improves the overall efficiency of the<br>  $X_{i,j}(t) = \frac{1}{3}[X_{r1}(t) + X_{r2}(t) + X_{r3}(t) + le'vy]$  (

$$
X_{i,j}(t) = \frac{1}{3} [X_{r1}(t) + X_{r2}(t) + X_{r3}(t) + le'vy] \tag{17}
$$

a. But also improves the overall efficiency of<br> *A.*  $A_{i,j}(t) = \frac{1}{3} [X_{r1}(t) + X_{r2}(t) + X_{r3}(t) + le'vy]$  (1)<br>
there Lévy is a D-dimensional vector generated by<br>
there Lévy is a D-dimensional vector generated by<br> *A.* Benchmark  $X_{i,j}(t) = \frac{1}{3}[X_{r1}(t) + X_{r2}(t) + X_{r3}(t) + le'vy]$  (17) To compare the HGSO and<br>
unlitative analysis of the<br>
convergence characteristics und the composite function<br>
Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequa  $X_{i,j}(t) = \frac{1}{3}[X_{r1}(t) + X_{r2}(t) + X_{r3}(t) + le'vy]$  (17) unditative analysis of the HGSO and<br>convergence characteristics users of the composite function<br>and the composite function surface that the composite function<br>and the com  $A_{i,j}(t) = \frac{1}{3} [A_{m1}(t) + A_{m2}(t) + A_{m3}(t) + te^{ij}]$  qualitative analysis<br>convergence character<br>and the composite function suite. Popula<br>Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal<br>performance of optin<br>andom Where Lévy is a D-dimensional vector generated by the<br>
Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal<br>
Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal<br>
The CEC of optimizary and mumbers.<br>
IV Where Lévy is a D-dimensional vector generated by the<br>
Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal<br>
performance of optimization<br>
random numbers.<br>
IV. RESULTS OF EXPERIMENT AND STATISTICAL ANALYSIS<br>
4. B where Levy is a D-dimensional vector generated by the<br>
Lévy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal<br>
algorithm's ability to<br>
random numbers.<br>
IV. RESULTS OF EXPERIMENT AND STATISTICAL ANALYSIS<br>
IV. RESUL Levy flight operator,  $rr_1$ ,  $rr_2$  and  $rr_3$  are three unequal pro-<br>
random numbers.<br>
IV. RESULTS OF EXPERIMENT AND STATISTICAL ANALYSIS quered to verify and evaluate the performance of E\_HGSO and<br>
its comparison algorith *B. Sensitivity analysis of E\_HGSO*<br> *B. Sensitivity and evaluate the performance of E\_HGSO and*<br> *B. Sensity and evaluate the performance of E\_HGSO and*<br>
comparison algorithms. Different types of functions can<br>
evaluate From the description of the E\_HGSO, *α* and *β* affect both<br>
this group and between-group search. In this space, CEC2017 benchmark functions [41] are<br>
duo verify and evaluate the performance of E\_HGSO and<br>
comparison algo *A. Benchmark functions*<br>
In this paper, CEC2017 benchmark functions [41] are<br>
used to verify and evaluate the performance of E\_HGSO and<br>
its comparison algorithms. Different types of functions can<br>
effectively check the

population diversity in the algorithm, and the algorithm<br>tends to fall into a local optimum. For this disadvantage, this<br>paper designs a new prey encircling formula that introduces<br>two stochastic gases, adding diversity a tends to fall into a local optimum. For this disadvantage, this<br>paper designs a new prey encircling formula that introduces<br>two stochastic gases, adding diversity and randomness to the<br>search, as shown in equation (16).<br>paper designs a new prey encircling formula that introduces<br>two stochastic gases, adding diversity and randomness to the<br>search, as shown in equation (16).<br> $(2\pi r) \gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{r/2}(t))]$  (16)<br>the sensitivity of t two stochastic gases, adding diversity and randomness to the<br>search, as shown in equation (16).<br> $2\pi r \gamma \gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{r/2}(t))]$  (16)<br>the sensitivity of these two parameters of E\_HGSO is<br>analysed. In performing the search, as shown in equation (16).<br>  $(2\pi r)\gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{r/2}(t))]$  (16)<br>
the sensitivity of these two parameters of E\_HGSO is<br>
analysed. In performing the sensitivity analysis, we select<br>
different types of functi  $(2\pi r) \gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{rr2}(t))]$  (16)<br>the sensitivity of these two parameters of E\_HGSO is<br>analysed. In performing the sensitivity analysis, we select<br>different types of functions from CEC2017 as evaluation<br>metrics  $(2\pi r)\gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{rr2}(t))]$ <br>the sensitivity of these two parameters of E\_H(<br>analysed. In performing the sensitivity analysis, we<br>different types of functions from CEC2017 as eva<br>metrics and run the algorithm sev  $r$ ) $\gamma \times X_{best}(t) - (1 + S_{i,j}(t) \times X_{rr2}(t))]$  (16)<br>
E sensitivity of these two parameters of E\_HGSO is<br>
alysed. In performing the sensitivity analysis, we select<br>
fferent types of functions from CEC2017 as evaluation<br>
trics and ru performance of E\_HGSO under the Values of analysed.<br>
the sensitivity of these two parameters of E\_HGSO is<br>
analysed. In performing the sensitivity analysis, we select<br>
different types of functions from CEC2017 as evaluati the sensitivity of these two parameters of *E\_HGSO* is<br>analysed. In performing the sensitivity analysis, we select<br>different types of functions from CEC2017 as evaluation<br>metrics and run the algorithm several times with d the sensitivity of these two parameters of E\_HGSO is<br>analysed. In performing the sensitivity analysis, we select<br>different types of functions from CEC2017 as evaluation<br>metrics and run the algorithm several times with dif *E.* sensitivity of these two parameters of E\_HGSO is alysed. In performing the sensitivity analysis, we select fferent types of functions from CEC2017 as evaluation etrics and run the algorithm several times with differe fferent types of functions from CEC2017 as evaluation<br>trics and run the algorithm several times with different<br>rameter combinations. The combination of  $\alpha$  and  $\beta$ <br>rameters with the best overall performance was selected

# *E\_HGSO*

To compare the HGSO and E\_HGSO, we will perform a<br>qualitative analysis of their population diversity and E HGSO<br>  $E = HGSO$ <br>  $E = HGSO$ <br>  $E = HGSO$ <br>
To compare the HGSO and<br>
convergence characteristics used<br>
there Lévy is a D-dimensional vector generated by the<br>
there Lévy is a D-dimensional vector generated by the<br>
there inciton sub metrics and run the algorithm several times with different<br>parameter combinations. The combination of  $\alpha$  and  $\beta$ <br>parameters with the best overall performance was selected<br>as the initial parameters of E\_HGSO. This metho parameter combinations. The combination of  $\alpha$  and  $\beta$ <br>parameters with the best overall performance was selected<br>as the initial parameters of E\_HGSO. This method is often<br>used in many studies.<br>From Fig.1, it can be seen parameters with the best overall performance was selected<br>as the initial parameters of E\_HGSO. This method is often<br>used in many studies.<br>From Fig.1, it can be seen that the comprehensive<br>performance of E\_HGSO under the P as the initial parameters of E\_HGSO. This method is often<br>used in many studies.<br>From Fig.1, it can be seen that the comprehensive<br>performance of E\_HGSO under the P31 parameter<br>combination is the best. Therefore, the value used in many studies.<br>
From Fig.1, it can be seen that the comprehensive<br>
performance of E\_HGSO under the P31 parameter<br>
combination is the best. Therefore, the values of  $\alpha$  and  $\beta$  in<br>
this paper are set to 4 and 0.4, From Fig.1, it can be seen that the comprehensive<br>performance of E\_HGSO under the P31 parameter<br>combination is the best. Therefore, the values of  $\alpha$  and  $\beta$  in<br>this paper are set to 4 and 0.4, respectively.<br>C. Qualitat performance of E\_HGSO under the P31 parameter<br>combination is the best. Therefore, the values of  $\alpha$  and  $\beta$  in<br>this paper are set to 4 and 0.4, respectively.<br>*C. Qualitative comparison between HGSO and*<br>*E\_HGSO*<br>To co combination is the best. Therefore, the values of  $\alpha$  and  $\beta$  in<br>this paper are set to 4 and 0.4, respectively.<br>C. Qualitative comparison between HGSO and<br>E\_HGSO<br>To compare the HGSO and E\_HGSO, we will perform a<br>qualita of these two parameters of E\_HGSO is<br>forming the sensitivity analysis, we select<br>of functions from CEC2017 as evaluation<br>the algorithm several times with different<br>intations. The combination of  $\alpha$  and  $\beta$ <br>the best over ensitivity of these two parameters of E\_HGSO is<br>estal. In performing the sensitivity analysis, we select<br>ent types of functions from CEC2017 as evaluation<br>cs and run the algorithm several times with different<br>er combinati To compare the HGSO and E\_HGSO, we will perform a<br>qualitative analysis of their population diversity and<br>convergence characteristics using the unimodal function  $f_3$ <br>and the composite function  $f_{10}$  from the CEC2017 te qualitative analysis of their population diversity and<br>convergence characteristics using the unimodal function  $f_3$ <br>and the composite function  $f_{10}$  from the CEC2017 test<br>function suite. Population diversity is a cruci on diversity and<br>imodal function  $f_3$ <br>the CEC2017 test<br>rucial factor in the<br>as it reflects the<br>space and avoid<br>diversity can be<br> $f$ ) –  $X^g$  ||) (18)<br>tion,  $X_i(t)$  denotes<br> $g$  denotes the best<br>on are defined as: convergence characteristics using the unimodal function  $j_3$ <br>and the composite function  $f_{10}$  from the CEC2017 test<br>function suite. Population diversity is a crucial factor in the<br>performance of optimization algorithms d the composite function  $f_{10}$  from the CEC2017 test<br>nction suite. Population diversity is a crucial factor in the<br>formance of optimization algorithms, as it reflects the<br>gorithm's ability to explore the search space an it can be seen that the comprehensive<br>f E-HGSO under the P31 parameter<br>the best. Therefore, the values of  $\alpha$  and  $\beta$  in<br>t to 4 and 0.4, respectively.<br>we *comparison between HGSO and*<br>he HGSO and E\_HGSO, we will perform HGSO under the P31 parameter<br>
st. Therefore, the values of  $\alpha$  and  $\beta$  in<br>
and 0.4, respectively.<br>
parison between HGSO and<br>
SSO and E\_HGSO, we will perform a<br>
of their population diversity and<br>
of their population dive the cost: network, the valuate of the damage of the to 4 and 0.4, respectively.<br> *ie comparison between HGSO and*<br> *ie* From Fig.1, it can be seen that the comprehensive<br>
frommate of E\_HGSO under the P31 parameter<br>
fromation is the best. Therefore, the values of *a* and *f* in<br>
is paper are set to 4 and 0.4, respectively.<br> *E\_HGSO*<br> *D* co *dis* is paper are set to 4 and 0.4, respectively.<br> *dis* paper are set to 4 and 0.4, respectively.<br> *C.* Qualitative comparison between HGSO and<br> *E\_HGSO*<br> **C.** Qualitative comparison between HGSO and<br> *d d*  $E$ -HGSO<br> sized in many studies.<br>
From Fig.1, it can be seen that the comprehensive<br>
From Fig.1, it can be seen that the comprehensive<br>
corpoformance of E\_HGSO under the P31 parameter<br>
combination is the best. Therefore, the values

$$
Diversity(t) = \frac{1}{N}sqrt(\sum_{i=1}^{N} ||X_i(t) - X^g||) \quad (18)
$$

$$
\begin{cases}\nExploration(t) = \frac{div(t)}{\max(div)} \times 100 \\
Explosition(t) = \left| \frac{div(t) - \max(div)}{\max(div)} \right| \times 100\n\end{cases} (19)
$$

## **Engineering Letters Engineering Eccuers**

**Example 1**<br>TABLE I<br>SUSED FOR PARAMETER SELECTION<br> $f(x)$ <br> $f_1$ **Engineering Letters**<br>
TABLE I<br>
DIMENSION OF FUNCTIONS USED FOR PARAMETER SELECTION<br>
Type *f*(*x*) Dimension<br> *f*<sub>1</sub> 20<br>
all functions *f*<sub>1</sub> **Engineering Letters**<br>
TABLE I<br>
DIMENSION OF FUNCTIONS USED FOR PARAMETER SELECTION<br>
Type<br>  $f(x)$  Dimension<br>
Unimodal functions<br>  $f_1$  20<br>  $f_2$  10<br>
multimodal functions<br>  $f_3$  20<br>  $f_4$  10 Engineering Le<br>
TABLE I<br>
DIMENSION OF FUNCTIONS USED FOR PA<br>
Type<br>
Unimodal functions<br>
multimodal functions<br>
Utchesid functions  $f_2$  10 *f*<sup>3</sup> 20 *f<sup>4</sup>* 10 *f<sup>5</sup>* 10 TABLE I<br>
Type<br>
Type<br>
Inimodal functions<br>
ultimodal functions<br>
Hybrid functions<br>
Hybrid functions *f<sup>6</sup>* 20 *f<sup>7</sup>* 20 *f<sup>8</sup>* 20 Type<br>Unimodal functions<br>multimodal functions<br>Hybrid functions<br>Composition functions<br>TARI F II *f<sup>9</sup>* 10 *f*<sub>10</sub> 10 *f*<sup>11</sup> 20 *f<sup>12</sup>* 20  $f_s$ <br>  $f_s$ <br>  $f_s$ <br>  $f_s$ <br>  $f_s$ <br>  $f_s$ <br>  $f_0$ <br>  $f_{10}$ <br>  $f_{11}$ <br>  $f_{12}$ <br>
TABLE II<br>
TER COMBINATION OF E\_HGSO<br>
TER COMBINATION OF E\_HGSO ms  $f_7$ <br>  $f_8$  20<br>  $f_9$  10<br>
tions  $f_{10}$  10<br>  $f_{11}$  20<br>  $f_{12}$  20<br>
TABLE II<br>
DIFFERENT PARAMETER COMBINATION OF E\_HGSO<br>
Different parameter combinations<br>
3<br>
4<br>
5<br>
6<br>
7<br>
8  $\begin{array}{c|c}\n & f_3 \\
f_6 \\
f_7 \\
f_8 \\
f_9\n\end{array}$ <br>  $\begin{array}{c|c}\n & f_9 \\
 & f_{10} \\
 & f_{11} \\
 & f_{12}\n\end{array}$ <br>
TABLE II<br>
INT PARAMETER COMBINATION OF E\_HGSO<br>
Different parameter combinations<br>
3<br>
4<br>
5<br>
6<br>
7<br>
P3<br>
P4<br>
P5<br>
P6<br>
P7 *From the discretions*<br> *g g*<br> *g fg*<br> *g* 20<br> *g***<br>** *g***<br>** *g***<br>** *g***<br>** *g***<br>
<b>EXECU**<br> **EXECU**<br> **EXECU**<br>

	<b>TABLE I</b>		
		I OF FUNCTIONS USED FOR PARAMETER SELF	







0.7 1934 1950 1286 1191 1067 913 1105 993 1164<br>
0.8 1845 1794 1204 1068 985 1229 1127 1187 1115 168<br>
1822 1719 1487 1487 1488 1374 1487 1115 1487 1289 1374 1487 1487 1<br>
1 2 3 4 5 6 7 8 9 1<br>
1 12 12 1187 1198 1487 1487 148 **1794** 1204 1068 985 1229 1127 1187 1115<br> **1898** 1845 1794 1204 1068 985 1229 1127 1187 1115<br> **1898** 1922 1719 1487 1487 1487 1289 1374 1487 1289 1374 1487 1289 1374 1487 1289 1374 1487 1289 1374 1487 1289 1374 1487 1289 0.8 1845 1794 1204 1068 985 1229 1127 1187 1115<br>
0.9 1922 1719 1487 1477 1488 1367 1229 1374 1487<br>
1229 1374 **1922** 1719 1487 1487 1487 1488 1367 1289 1374 1489 1374 1483 1374 1483 1374 1483 1374 1483 14 2 3 4 5 6 7 8 Fig.1. The sensitivity analysis results of E\_HGSO for different types of The observations made from Fig.2 and 3 <sup>0.9</sup> <sup>1922</sup> <sup>1719</sup> <sup>1487</sup> <sup>1</sup> <sup>2</sup> <sup>3</sup> <sup>4</sup> <sup>5</sup> <sup>6</sup> <sup>7</sup> <sup>8</sup> <sup>9</sup><br>
Fig.1. The sensitivity analysis results of E\_HGSO for different types of fun<br>
The observations made from Fig.2 and 3 highlight notable more dominant, which co<br>
differences between the

accuracy. Based on in-depth analysis of the convergence<br>accuracy. Based on in-depth analysis of the convergence<br>accuracy. Based on in-depth analysis of the convergence<br>accuracy. Based on in-depth analysis of the convergenc <sup>260</sup><br>
<sup>360</sup><br>
<sup>367</sup><br>
<sup>1105</sup><br>
<sup>1105</sup><br>
<sup>1106</sup><br>
<sup>1107</sup><br>
<sup>1187</sup><br>
<sup>1115</sup><br>
<sup>1000</sup><br>
<sup>1000</sup><br> 913 1105 993 1164<br>
1229 1127 1187 1115<br>
1367 1289 1374 1487 1115<br>
6 7 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergence<br>
accuracy. Based on in-depth analysis of the converg 913 1105 993 1164<br>
1229 1127 1187 1115<br>
1367 1289 1374 1487<br>
6 7 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergence<br>
accuracy. Based on in-depth analysis of the convergence 1229 1127 1187 1115<br>
1387 1289 1374 1487 1115<br>
6 7 8 9 1600<br>
HGSO for different types of function<br>
1600<br>
16 1229 1127 1187 1115<br>
1367 1289 1374 1487 1115<br>
6 7 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergence<br>
accuracy. Based on in-depth analysis of the convergence<br>
curves, we f 1367 1289 1374 1487 160<br>
6 7 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergence<br>
accuracy. Based on in-depth analysis of the convergence<br>
curves, we found that the E\_HGSO al <sup>1367</sup> <sup>1289</sup> <sup>1374</sup> <sup>1487</sup> **1487 1600**<br>
6 <sup>7</sup> 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergence<br>
accuracy. Based on in-depth analysis of the convergence<br>
curves, we fou 6 7 8 9<br>
HGSO for different types of function<br>
more dominant, which contributes to improved convergene<br>
accuracy. Based on in-depth analysis of the convergene<br>
curves, we found that the E\_HGSO algorithm exhibit<br>
superior



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# **Engineering Letters Engineering Eccuers**



GHGSO<br>
E\_HGSO<br>  $E$ \_HGSO<br>  $p$ -value<br>
The analysis of the convergence accuracy cur<br>
that although the final outcomes are generally com<br>
closer examination through the zoomed-in graph re<br>
the results of the E\_HGSO exhibit gr

shown<br>
7.8276<br>
3.2069<br>
1.4138<br>
1.0728e-32<br>
D. Compare to other algorithms<br>
To verify the performance of the E\_HGSO algorithm, we<br>
compared it with the HGSO and QHGSO algorithms, as well<br>
as six other popular algorithms on 7.8276<br>3.2069<br>1.4138<br>1.0728e-32<br>**D. Compare to other algorithms**<br>To verify the performance of the E\_HGSO algorithm, we<br>compared it with the HGSO and QHGSO algorithms, as well<br>as six other popular algorithms on the CEC2017 3.2069<br>
1.4138<br>
1.0728e-32<br>
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To verify the performance of the E\_HGSO algorithm, we<br>
compared it with the HGSO and QHGSO algorithms, as well<br>
as six other popular algorithms on the CEC2017 ben

					<b>Engineering Letters</b>					
					<b>TABLE IV</b>					
							RESULTS OF COMPARING ALGORITHMS ON THE CEC2017 BENCHMARK FUNCTION (D=50)			
f(x)	Index	<b>TS22</b>	<b>HBA</b>	FDA	AHA	SO	<b>BWO</b>	<b>HGSO</b>	QHGSO	E HGSO
$f_I$	Mean	5.0467E+07	4.0720E+06	1.3641E+09	1.9665E+05	8.9469E+05	$1.0045E+11$	4.2407E+10	4.3082E+03	3.8899E+03
	Std	1.3110E+07	2.3629E+06	5.3791E+08	2.6273E+05	1.1299E+06	3.8826E+09	7.1478E+09	$6.3049E+03$	3.5388E+03
	<b>Best</b>	3.1725E+07	1.5259E+06	5.7839E+08	4.4219E+04	4.0069E+04	9.1458E+10	2.7898E+10	$1.0051E+02$	5.6110E+02
	Rank	6	5	$\tau$	3	$\overline{4}$	9	8	2	1
fз	Mean	$1.0903E + 05$	1.2964E+05	6.7132E+04	3.8944E+04	1.2831E+05	1.9604E+05	1.4848E+05	4.3568E+04	4.4604E+04
	Std	1.3495E+04	$1.6664E + 04$	1.3571E+04	8.9288E+03	1.2966E+04	1.7387E+04	8.2908E+03	$1.1641E+04$	$1.1351E+04$
	<b>Best</b>	8.2552E+04	$1.0461E + 05$	3.9045E+04	2.1757E+04	9.6936E+04	1.6306E+05	1.2890E+05	2.5138E+04	2.6585E+04
	Rank	5	7	4	1	6	9	8	2	3
f4	Mean	5.7336E+02	5.5927E+02	6.7770E+02	5.5229E+02	5.6634E+02	2.9846E+04	8.9138E+03	5.2109E+02	5.0436E+02
	Std	2.2978E+01	5.1383E+01	4.7657E+01	5.1601E+01	5.2665E+01	2.4544E+03	1.9489E+03	3.7593E+01	5.4080E+01
	Best	5.0061E+02	4.7269E+02	5.7918E+02	4.4995E+02	4.2917E+02	2.6155E+04	5.5490E+03	4.7525E+02	4.2277E+02
	Rank	6	$\overline{4}$	7	3	5	9	8	$\mathfrak{2}$	1
f5	Mean	8.0126E+02	7.1736E+02	8.0796E+02	7.9673E+02	6.3588E+02	$1.1693E+03$	$1.0697E + 03$	6.3275E+02	5.5655E+02
	Std	2.7971E+01	3.0554E+01	5.4872E+01	3.1221E+01	2.0849E+01	2.2951E+01	2.1705E+01	5.6397E+01	1.4449E+01
	<b>Best</b>	7.3971E+02	6.4211E+02	7.0205E+02	7.3979E+02	5.7611E+02	1.1064E+03	$1.0172E + 03$	5.9651E+02	5.3283E+02
	Rank	6	$\overline{4}$	7	5	3	9	8	2	1
f6	Mean	6.2790E+02 6.5889E+00	$6.1063E+02$	6.6336E+02 5.7539E+00	6.1031E+02	6.0578E+02	6.9883E+02	6.8211E+02 6.7293E+00	6.0069E+02	$6.0007E + 02$
	Std		$6.5621E+00$		9.9865E+00	3.1244E+00	3.3280E+00		5.7897E-01	1.1680E-01
	Best	6.1620E+02	$6.0124E+02$	6.5001E+02	$6.0044E + 02$	6.0127E+02	6.8612E+02 9	6.6606E+02	$6.0016E+02$	$6.0001E+02$
	Rank	6 1.1945E+03	5 1.0522E+03	$\tau$ 1.1964E+03	4 1.2991E+03	3 9.0583E+02	1.9156E+03	8 1.7023E+03	2 9.3761E+02	1 8.0530E+02
f7	Mean	5.6633E+01	5.6900E+01	7.0695E+01	1.3064E+02	3.6210E+01	4.5012E+01	9.4896E+01	6.4798E+01	1.2994E+01
	Std	1.0868E+03	9.8468E+02	1.0877E+03	1.1607E+03	8.4510E+02	1.8338E+03	1.4963E+03	8.4211E+02	7.8365E+02
	<b>Best</b> Rank	5	$\overline{4}$	6	7	$\overline{c}$	9	8	3	1
	Mean	$1.1237E + 03$	$1.0441E+03$	1.1086E+03	1.1267E+03	9.4128E+02	1.4837E+03	1.4109E+03	9.3797E+02	8.5976E+02
f8	Std	2.9783E+01	6.0920E+01	4.9144E+01	3.9253E+01	1.9572E+01	2.4079E+01	2.2455E+01	2.5914E+01	$1.1804E + 01$
		1.0718E+03	9.5292E+02	1.0348E+03	1.0516E+03	8.9883E+02	1.4228E+03	1.3630E+03	9.0008E+02	8.3781E+02
	Best Rank	6	4	5	$\tau$	3	9	8	2	1
		1.5959E+04	9.5070E+03	1.0826E+04	1.0608E+04	1.9005E+03	3.6806E+04	2.8414E+04	1.3676E+03	$9.1268E + 02$
f9.	Mean Std	$1.8104E + 03$	$3.2895E+03$	$4.0149E + 03$	$2.4563E+03$	6.8929E+02	$2.0277E + 03$	$2.6945E+03$	5.1135E+02	1.5790E+01
	Best	$1.1115E + 04$	$4.5223E+03$	$5.9037E + 03$	$6.1102E + 03$	1.3813E+03	$3.1611E+04$	2.4197E+04	9.8130E+02	$9.0054E + 02$
	Rank	7	$\overline{4}$	6	5	$\overline{3}$	9	8	$\overline{2}$	$\mathbf{1}$
$f_{10}$	Mean	7.2256E+03	7.4491E+03	$9.4600E + 03$	$6.2099E+03$	5.4231E+03	1.4494E+04	$1.3883E + 04$	$1.3844E+04$	$6.7160E + 03$
	Std	5.9467E+02	2.4416E+03	8.5528E+02	8.7344E+02	$1.6821E + 03$	4.4110E+02	5.3178E+02	7.5078E+02	$1.0808E + 03$
	Best	$6.1812E+03$	5.4022E+03	7.7380E+03	$5.0095E + 03$	$4.0029E+03$	1.3116E+04	$1.2337E + 04$	1.1158E+04	$3.9975E + 03$
	Rank	$\overline{4}$	5	6	2	$\blacksquare$	9	8	7	3
$f_{II}$	Mean	$1.6119E+03$	$1.4165E+03$	$1.5641E+03$	$1.2671E + 03$	1.3785E+03	$2.0002E + 04$	$7.1146E + 03$	$1.1948E + 03$	1.1717E+03
	Std	$1.9972E+02$	7.6492E+01	$1.1658E+02$	$4.1564E + 01$	1.0099E+02	$2.1222E+03$	$1.1032E + 03$	$4.6367E + 01$	$2.4690E+01$
	Best	$1.3658E + 03$	$1.2991E+03$	$1.3134E+03$	$1.2102E + 03$	$1.2314E + 03$	1.4481E+04	5.1589E+03	$1.1514E+03$	$1.1352E+03$
	Rank	$\overline{7}$	$5\overline{)}$	6	$\overline{3}$	$\overline{4}$	9	8	$\overline{2}$	$\blacksquare$
$f_{12}$	Mean	1.6116E+07	7.5670E+06	$4.6460E+07$	4.6598E+06	4.1380E+06	$5.1212E+10$	$1.3160E+10$	$1.4403E + 06$	$3.2523E + 06$
	Std	$6.1552E + 06$	$4.6226E + 06$	$2.0397E+07$	$2.0030E + 06$	2.6387E+06	8.2247E+09	$3.7722E + 09$	$9.0879E + 05$	1.5757E+06
	Best	$5.0264E + 06$	2.2004E+06	1.3216E+07	$1.3912E + 06$	1.4595E+06	$3.1126E+10$	$9.0912E + 09$	$4.5131E+05$	$1.0010E + 06$
	Rank	6	5	7	$\overline{4}$	$\overline{3}$	9	8	$\overline{1}$	2
$f_{13}$	Mean	2.5835E+04	2.8813E+04	$4.6295E+04$	1.0763E+04	$3.0548E + 04$	$2.8835E+10$	3.2579E+09	$4.9576E+03$	5.7924E+03
	Std	$6.5788E + 03$	2.2694E+04	2.8280E+04	1.0165E+04	$2.3626E + 04$	$6.0997E+09$	7.9992E+08	$4.3371E+03$	$2.5089E + 03$
	Best	$1.4169E + 04$	3.7233E+03	1.4894E+04	$2.5306E+03$	8.2222E+03	$1.3706E+10$	$1.8047E + 09$	$1.4265E+03$	$3.2132E + 03$
	Rank	4	5	7	$\mathbf{3}$	$6\overline{6}$	9	8	$\blacksquare$	2
$f_{14}$	Mean	8.4709E+05	1.4273E+05	$6.3328E+04$	1.3600E+05	6.3258E+04	$3.2999E+07$	4.4556E+06	8.9367E+04	9.2519E+04
	Std	5.3562E+05	8.6058E+04	$6.1835E+04$	1.0280E+05	5.5343E+04	1.4235E+07	$1.1044E + 06$	$4.6108E + 04$	6.3578E+04
	Best	$4.2088E + 04$	2.7848E+04	$3.0987E + 03$	7.0458E+03	$5.0904E + 03$	$1.0471E+07$	$2.4029E + 06$	$2.1208E + 04$	1.3495E+04
	Rank	$7\overline{ }$	6	2	5	$\blacksquare$	9	8	3	4
$f_{15}$	Mean	8.3284E+03	$1.6451E+04$	$1.2670E + 04$	1.3815E+04	$1.0058E + 04$	4.5098E+09	$4.4602E + 08$	$5.3096E+03$	7.7054E+03
	Std	4.5195E+03	1.5976E+04	$6.3548E+03$	$6.4991E+03$	5.6581E+03	$1.0091E + 09$	$1.6977E + 08$	$4.2685E+03$	$3.9065E+03$
	<b>Best</b>	$2.8049E+03$	2.9758E+03	$2.7942E+03$	2.1588E+03	3.7998E+03	2.8857E+09	$1.6782E + 08$	$1.5836E+03$	$2.0484E+03$
	Rank	$\mathbf{3}$	$7\overline{ }$	5	6	$\overline{4}$	9	8	-1	2
$f_{16}$	Mean	$3.1906E + 03$	3.8253E+03	$3.5006E+03$	$3.2990E+03$	2.8448E+03	7.9349E+03	$5.5097E+03$	$2.9038E + 03$	$2.6354E+03$
	Std	3.1995E+02	$1.0916E + 03$	$4.7662E+02$	$3.6932E+02$	$2.6655E+02$	5.5200E+02	$1.9917E+02$	$6.3660E+02$	$3.6722E+02$
						2.3230E+03 2.6676E+03 2.4691E+03	$6.1835E+03$	$4.8928E + 03$	$2.0434E + 03$	$2.1466E+03$

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						<b>Engineering Letters</b>				
						<b>TABLE V</b>				
							RESULTS OF COMPARING ALGORITHMS ON THE CEC2017 BENCHMARK FUNCTION (D=100)			
f(x)	Index	<b>TS22</b>	<b>HBA</b>	FDA	AHA	<sub>SO</sub>	<b>BWO</b>	<b>HGSO</b>	QHGSO	E HGSO
$f_I$	Mean	1.7726E+09	3.5173E+09	2.2732E+10	2.4507E+08	1.2680E+07	2.6722E+11	$1.6462E+11$	5.3570E+04	3.9760E+04
	Std	2.1151E+08	1.7941E+09	3.8859E+09	1.0235E+09	7.4599E+06	6.3959E+09	1.7326E+10	1.2800E+05	1.1985E+04
	<b>Best</b>	1.3219E+09	1.1495E+09	$1.6677E+10$	2.1467E+07	3.6474E+06	2.4629E+11	1.2459E+11	2.9385E+03	1.9781E+04
	Rank	5	6	$\tau$	4	3	9	8	$\overline{c}$	1
$\int$ 3	Mean	3.0394E+05	4.0491E+05	2.5760E+05	1.9383E+05	3.1806E+05	4.5509E+05	3.2674E+05	3.3068E+05	3.3940E+05
	Std	1.3798E+04 2.7413E+05	5.6939E+04 3.2543E+05	2.8372E+04 2.0468E+05	1.5861E+04 1.5905E+05	2.1759E+04 2.2964E+05	1.4224E+05 3.4811E+05	1.3648E+04 2.9964E+05	3.7037E+04 2.6598E+05	4.3430E+04 2.2158E+05
	<b>Best</b> Rank	3	8	$\overline{2}$	1	4	9	5	6	7
$f_4$	Mean	1.0839E+03	1.2651E+03	2.2510E+03	$1.0215E + 03$	7.5159E+02	1.0895E+05	3.2301E+04	7.3367E+02	6.9432E+02
	Std	4.6361E+01	1.1842E+02	4.1669E+02	9.2692E+01	5.4313E+01	7.6207E+03	6.4003E+03	4.3995E+01	5.1198E+01
	<b>Best</b>	9.7748E+02	$1.0201E+03$	1.4717E+03	8.7738E+02	6.8254E+02	8.9847E+04	1.9248E+04	6.4728E+02	5.5317E+02
	Rank	5	6	7	4	3	9	8	$\mathfrak{2}$	1
f5	Mean	1.4484E+03	1.2212E+03	1.3723E+03	1.3094E+03	8.3998E+02	2.1507E+03	1.8997E+03	9.7710E+02	6.7716E+02
	Std	4.7078E+01	5.8395E+01	1.0722E+02	$6.2002E+01$	3.4476E+01	2.9606E+01	4.3962E+01	1.2702E+02	3.0084E+01
	<b>Best</b>	1.3085E+03	1.1248E+03	1.1912E+03	1.1551E+03	7.5311E+02	2.0824E+03	1.8102E+03	8.0335E+02	$6.0649E+02$
	Rank	$\tau$	4	6	5	$\overline{c}$	9	8	3	1
f6	Mean	6.5688E+02	6.3517E+02	6.7298E+02	6.2679E+02	6.1938E+02	7.1548E+02	6.9998E+02	6.0755E+02	$6.0021E+02$
	Std	4.4501E+00	7.4057E+00	4.5269E+00	9.6939E+00	3.6834E+00	2.5224E+00	3.5140E+00	1.7970E+00	2.4678E-01
	<b>Best</b>	6.4716E+02	$6.2015E+02$	6.6298E+02	$6.1012E + 02$	6.1099E+02	7.1099E+02	6.9066E+02	6.0353E+02	$6.0006E + 02$
	Rank	6	5	$7\phantom{.0}$	4	3	9	8	2	1
$f_7$	Mean	2.6060E+03	2.2256E+03	2.5479E+03	$2.6046E + 03$	1.2477E+03	3.9613E+03	3.4275E+03	1.4678E+03	9.8848E+02
	Std	1.3071E+02	2.1272E+02	1.8786E+02	3.3353E+02	6.3119E+01	6.4586E+01	1.7519E+02	$1.1702E+02$	3.1311E+01
	<b>Best</b>	2.4371E+03	1.8074E+03	2.1711E+03	2.0511E+03	1.1732E+03	3.8064E+03	3.0191E+03	1.1790E+03	9.1796E+02
	Rank	$\tau$	4	5	6	$\overline{c}$	9	8	3	1
f8	Mean	1.8343E+03	1.5253E+03	1.7015E+03	1.6966E+03	1.1408E+03	2.6506E+03	2.2970E+03	1.2690E+03	9.7842E+02
	Std	5.4774E+01	7.5541E+01	1.0187E+02	1.0583E+02	3.7740E+01	4.3042E+01	5.3760E+01	1.2094E+02	3.5206E+01
	<b>Best</b>	$1.6494E+03$	1.4216E+03	1.4869E+03	1.4809E+03	1.0692E+03	2.5130E+03	2.1761E+03	$1.1044E+03$	9.2141E+02
	Rank	7	4	6	5	2	9	8	3	1
f9	Mean	4.8013E+04	5.2471E+04	4.1744E+04	2.4169E+04	7.0573E+03	8.4510E+04	7.1145E+04	1.8151E+04	$1.0400E + 03$
	Std	$2.2842E+03$	7.0270E+03	$6.3714E+03$	$9.9671E+02$	1.9728E+03	3.5847E+03	$4.2620E + 03$	$1.2408E + 04$	$1.1433E+02$
	<b>Best</b>	4.4275E+04	3.8119E+04	2.5576E+04	2.1215E+04	4.7179E+03	7.7406E+04	$6.2679E + 04$	5.1367E+03	9.2627E+02
	Rank	6	7	5	$\overline{4}$	2	9	8	3	1
$f_{10}$	Mean	1.8675E+04	2.4699E+04	2.1400E+04 $1.2156E + 03$	1.4678E+04	2.6690E+04	3.3222E+04	2.8846E+04	$3.1308E + 04$	$1.3945E+04$
	Std Best	$9.6106E + 02$ $1.7126E + 04$	4.5190E+03 $1.6571E+04$	1.8908E+04	1.5798E+03 $1.0915E+04$	2.7706E+03 2.2147E+04	6.7858E+02 3.1759E+04	$1.0260E + 03$ $2.7002E + 04$	5.6450E+02 $3.0306E + 04$	$1.6036E + 03$ $1.0113E + 04$
	Rank	3	5	$\overline{4}$	$\overline{2}$	6	9	$7\overline{ }$	8	1
$f_{II}$	Mean	$2.5026E + 04$	$4.6736E + 04$	3.2442E+04	2.8238E+04	3.0672E+04	$4.6012E + 05$	1.3934E+05	7.8204E+03	$3.0208E + 03$
	Std	$6.5551E+03$	9.5768E+03	$7.2024E + 03$	$1.1408E + 04$	7.8230E+03	1.4909E+05	1.2970E+04	$4.5285E+03$	5.3217E+02
	Best	$1.2777E + 04$	3.5583E+04	$2.1162E + 04$	1.1397E+04	1.5406E+04	$3.1723E + 05$	$1.0192E + 05$	$3.1920E+03$	$2.2823E+03$
	Rank	3	$\tau$	6	$\overline{4}$	5 <sup>5</sup>	9	8	$\overline{2}$	$\mathbf{1}$
$f_{12}$	Mean	3.2149E+08	$2.2163E + 08$	1.7624E+09	6.3639E+07	$9.6005E + 07$	2.1173E+11	$6.7385E+10$	1.4993E+07	2.2154E+07
	Std	7.5053E+07	$5.2044E+07$	$4.7361E + 08$	$3.3909E+07$	4.2567E+07	$1.1253E+10$	1.4989E+10	5.4846E+06	7.9968E+06
	Best	$2.1656E + 08$	$1.3043E + 08$	$1.0374E + 09$	2.0765E+07	2.2066E+07	$1.9005E+11$	$3.3262E+10$	4.1786E+06	$1.0128E + 07$
	Rank	6	5	$7\phantom{.0}$	$\mathbf{3}$	$\overline{4}$	9	8	$\blacksquare$	2
$f_{13}$	Mean	8.5973E+05	$1.0463E + 05$	$1.1096E+07$	3.7974E+04	$6.6382E+04$	$4.8257E+10$	$9.9903E + 09$	$5.4165E+03$	1.2775E+04
	Std	$2.5913E+05$	$3.3862E + 05$	8.7010E+06	$2.4206E + 04$	6.5433E+04	4.3388E+09	$2.8021E+09$	3.7229E+03	$2.9283E+03$
	Best	4.8839E+05	$6.6599E+03$	1.3589E+06	$9.0915E+03$	$2.0203E + 04$	$3.4646E+10$	5.2612E+09	$1.7174E + 03$	8.4317E+03
	Rank	6	5	$7\phantom{.0}$	$\mathfrak{Z}$	$\overline{4}$	9	8	$\blacksquare$	2
$f_{14}$	Mean	$3.6613E + 06$	$2.0243E + 06$	$1.6768E + 06$	1.4545E+06	1.5570E+06	$1.0032E + 08$	$2.1829E+07$	$1.1659E + 06$	$9.6420E + 05$
	Std	8.2599E+05	7.3598E+05	9.4981E+05	$6.3300E + 05$	7.1287E+05	2.9933E+07	$4.4292E + 06$	$4.9469E+05$	$2.5516E+05$
	Best	$1.4239E + 06$	8.6491E+05	7.1055E+05	5.7804E+05	4.8115E+05	$3.6724E+07$	1.3871E+07	$5.3021E+05$	$4.6235E + 05$
	Rank	$7\overline{ }$	6	5 <sup>5</sup>	$\mathbf{3}$	$\overline{4}$	9	8	2	$\mathbf{1}$
$f_{15}$	Mean	5.1989E+04	1.2810E+04	$1.0310E + 05$	7.5219E+03	1.9898E+04	$2.5784E+10$	2.7497E+09	$3.7161E+03$	$4.7152E + 03$
	Std	1.3390E+04	$1.1944E + 04$	5.5101E+04	5.9482E+03	2.0820E+04	$3.2482E+09$	$8.0343E + 08$	$2.9103E+03$	1.2172E+03
	Best	$2.0434E + 04$	2.7659E+03	1.9195E+04	2.1367E+03	6.4179E+03	$1.5241E+10$	$1.0984E + 09$	1.7239E+03	$3.1211E+03$
	Rank	6	$\overline{4}$	$7\overline{ }$	$\mathbf{3}$	5 <sup>5</sup>	9	8	$\mathbf{1}$	$\overline{2}$
$f_{16}$	Mean	5.7828E+03	5.5894E+03	$6.8122E+03$	5.6335E+03	5.7068E+03	2.4343E+04	$1.3527E + 04$	7.3350E+03	$4.8470E + 03$
	Std	3.9898E+02	7.8154E+02	$4.3684E+02$	$6.2622E+02$	1.5711E+03	2.3693E+03	9.2290E+02	$2.0435E+03$	$6.0997E+02$
	Best	$4.9386E+03$	$3.9835E+03$	5.5973E+03	$4.3265E+03$	3.9297E+03		1.8888E+04   1.2046E+04	$4.3045E+03$	$3.4979E + 03$

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		<b>TS22</b>	<b>HBA</b>	<b>FDA</b>	<b>CONTINUED TABLE V</b> AHA	<sub>SO</sub>	<b>BWO</b>	<b>HGSO</b>	QHGSO	E HGSO
f(x)	Index Rank	5	2	6	3	$\overline{4}$	9	8	$\tau$	$\mathbf{1}$
$f_{17}$	Mean	$5.1413E+03$	5.3263E+03	5.6631E+03	5.1050E+03	4.4345E+03	1.1590E+07	2.1449E+04	5.6181E+03	$4.1470E + 03$
	Std	4.1836E+02	4.7711E+02	7.2421E+02	$5.1426E+02$	4.4748E+02	5.7951E+06	$6.8468E+03$	$1.1997E+03$	4.2745E+02
	Best	4.3593E+03	4.5342E+03	3.9741E+03	$4.3004E+03$	3.7082E+03	3.5977E+06	$1.0315E + 04$	$3.6412E + 03$	$3.3026E + 03$
	Rank	4	5	7	3	2	9	8	6	1
$f_{18}$	Mean	3.3650E+06	5.1964E+06	2.5429E+06	2.3641E+06	3.8067E+06	3.0654E+08	3.1638E+07	5.0683E+06	$1.5032E + 06$
	Std	9.3784E+05	2.4934E+06	$1.2266E+06$	1.1118E+06	$1.6241E + 06$	$1.1982E+08$	$6.7661E + 06$	2.7180E+06	$6.5392E+05$
	Best	$2.0190E + 06$	$2.6301E + 06$	5.6205E+05	$9.5083E + 05$	1.4691E+06	1.1891E+08	$1.6461E+07$	8.5633E+05	6.4898E+05
	Rank	$\overline{4}$	7	3	$\overline{2}$	5	9	8	6	1
$f_{I9}$	Mean	$6.7948E + 04$	7.5914E+03	5.6672E+05	6.4181E+04	2.9208E+04	2.5525E+10	2.7179E+09	$4.5156E+03$	$3.4420E + 03$
	Std	$2.6280E + 04$	5.8269E+03	3.0382E+05	2.9799E+05	3.3815E+04	2.8809E+09	8.4608E+08	2.7326E+03	9.5555E+02
	<b>Best</b>	1.9517E+04	2.8294E+03	$1.6119E+05$	$2.6697E+03$	$2.6824E+03$	$1.9871E+10$	$1.1205E+09$	$1.9995E+03$	2.4817E+03
	Rank	6	3	7	5	$\overline{4}$	9	8	2	1
$f_{20}$	Mean	5.0845E+03	5.1537E+03	5.8457E+03	5.3403E+03	5.8916E+03	8.1957E+03	7.2190E+03	7.0476E+03	4.3539E+03
	Std	3.5569E+02	7.2627E+02	5.5335E+02	5.8969E+02	$1.0532E+03$	3.1273E+02	3.5415E+02	8.4330E+02	4.5727E+02
	Best	4.2581E+03	$4.2233E+03$	5.0135E+03	$4.0012E+03$	3.9208E+03	7.3360E+03	$6.4405E+03$	$3.5074E+03$	$3.5120E + 03$
	Rank	2	3	5	4	6	9	8	7	1
	Mean	3.4825E+03	$3.0111E+03$	3.2226E+03	$3.0095E+03$	2.7252E+03	4.9805E+03	4.1528E+03	2.7529E+03	$2.4914E+03$
$f_{21}$	Std	1.1089E+02	$6.4004E+01$	$1.1747E+02$	$1.0591E+02$	$3.9652E + 01$	$9.2243E+01$	1.2150E+02	9.4975E+01	$2.3382E + 01$
	Best	$3.1481E + 03$	2.9124E+03	2.9688E+03	$2.8333E+03$	$2.5964E+03$	4.8466E+03	3.9085E+03	2.5447E+03	2.4459E+03
	Rank	$\tau$	5	6	4	2	9	8	3	$\mathbf{1}$
	Mean	2.2198E+04	2.6029E+04	2.4321E+04	1.8954E+04	2.6926E+04	3.5759E+04	3.2324E+04	3.3746E+04	$1.6135E + 04$
	Std	$1.0250E + 03$	3.9443E+03	1.4889E+03	$1.8456E+03$	5.1805E+03	$5.0026E + 02$	7.5458E+02	7.8877E+02	$1.6242E + 03$
	Best	$2.0381E + 04$	$1.8461E+04$	2.1234E+04	1.4953E+04	1.3887E+04	3.4771E+04	$3.0450E + 04$	$3.1804E+04$	$1.2001E + 04$
	Rank	3	5	4	2	6	9	7	8	1
	Mean	$3.8890E + 03$	3.5714E+03	$3.7993E+03$	$3.3552E+03$	$3.3612E+03$	$6.3120E+03$	$5.8992E + 03$	$3.2211E+03$	$3.0301E + 03$
	Std	$1.0514E + 02$	$4.6237E+02$	$1.3075E+02$	7.7857E+01	7.6539E+01	2.2757E+02	$1.9533E+02$	$8.0582E + 01$	$4.6852E+01$
	Best	$3.7367E + 03$	3.3091E+03	$3.6207E + 03$	$3.1957E+03$	3.2346E+03	5.7097E+03	5.5277E+03	3.1011E+03	$2.9434E + 03$
	Rank	7	5	6	3	$\overline{4}$	9	8	2	$\mathbf{1}$
	Mean	$4.6043E+03$	5.7436E+03	$4.5666E+03$	$4.2651E+03$	$4.0243E+03$	$1.0048E + 04$	8.5517E+03	$3.6864E + 03$	3.4739E+03
	Std	$1.3620E + 02$	$2.6233E+03$	1.9387E+02	$1.2696E+02$	8.3001E+01	$6.9047E+02$	$5.7942E+02$	9.7917E+01	$6.8061E+01$
		$4.3165E+03$						7.5678E+03		
	Best Rank	6	$3.8663E+03$ $\tau$	4.1474E+03 5	$4.0076E+03$ 4	3.8627E+03 3	8.4398E+03 9	8	$3.5423E+03$ $\overline{2}$	$3.3600E + 03$ 1
	Mean	3.7796E+03	3.9589E+03	4.8135E+03	$3.6619E + 03$	3.4806E+03	2.9258E+04	1.4307E+04	3.3751E+03	3.3422E+03
				3.8537E+02	9.1837E+01	5.9667E+01	1.4089E+03			
	Std	$6.5351E+01$ $3.6672E + 03$	$1.6883E+02$					$1.1628E + 03$ $1.1919E + 04$	$6.0355E+01$ 3.2731E+03	$5.0269E + 01$
	Best	5 <sup>5</sup>	$3.7204E + 03$ 6	$4.1093E+03$ $7\overline{ }$	$3.5024E+03$ $\overline{4}$	$3.3632E + 03$ 3 <sup>1</sup>	2.5937E+04 9	8	2	$3.2453E + 03$ -1
	Rank			1.9250E+04						
	Mean	$6.6174E + 03$	$1.5536E + 04$		1.8556E+04	1.2427E+04	5.2073E+04	$3.6299E + 04$	$1.0164E + 04$	8.3507E+03
	Std	3.5888E+03	$9.7665E+03$	1.7691E+03 1.5960E+04	6.9410E+03	7.9055E+02	1.1669E+03	$2.5906E+03$	8.4197E+02	$9.6413E+02$ $6.9578E + 03$
	Best	$5.0745E + 03$	1.1930E+04		$4.5742E+03$	$1.0609E + 04$	$5.0036E + 04$	$3.1551E + 04$	$8.0833E + 03$	
	Rank	$\blacksquare$	5	$7\overline{ }$	6	$\overline{4}$	9	8	$\mathbf{3}$	2
	Mean	3.7339E+03	4.6181E+03	4.1877E+03	$3.8974E+03$	3.7520E+03	$1.3273E + 04$	8.9646E+03	$3.5951E+03$	3.5317E+03
	Std	8.2458E+01	$1.7103E+03$	2.1511E+02	$1.1643E+02$	8.5377E+01	9.4258E+02	$8.6002E + 02$	$6.9604E+01$	7.8054E+01
	<b>Best</b>	$3.5744E + 03$	3.5136E+03	3.7237E+03	$3.6722E+03$	$3.6040E + 03$	$1.0945E + 04$	$7.1254E + 03$	$3.4406E+03$	$3.4310E + 03$
	Rank	$\mathbf{3}$	$7\overline{ }$	6	5	$\overline{4}$	9	8	$\overline{2}$	$\mathbf{1}$
	Mean	3.8725E+03	4.3229E+03	$6.3023E+03$	$3.9012E + 03$	$3.6506E+03$	2.8698E+04	$2.0340E + 04$	$3.5100E+03$	$3.5193E+03$
	Std	$6.5058E+01$	$2.9966E+02$	7.7313E+02	$2.2291E+02$	$4.3363E+01$	$1.0727E + 03$	$2.1194E+03$	3.4814E+01	$3.0408E + 01$
	<b>Best</b>	$3.7453E + 03$	3.8311E+03	$5.0351E+03$	$3.6507E + 03$	3.5358E+03	$2.6477E + 04$	1.4376E+04	3.4498E+03	$3.4406E+03$
	Rank	4	6	$7\phantom{.0}$	5	3	9	8	$\mathbf{1}$	2
	Mean	$7.5663E + 03$	$6.8469E+03$	9.2789E+03	7.0654E+03	6.9978E+03	8.0198E+05	$2.0022E + 04$	$6.2503E+03$	$5.0244E + 03$
	Std	3.3960E+02	$3.9495E+02$	8.3390E+02	7.3917E+02	5.5059E+02	$3.2353E + 05$	3.2784E+03	$6.7028E+02$	$6.4296E+02$
	Best	$6.8225E+03$	$6.1911E+03$	7.7768E+03	$5.6073E + 03$	$5.6149E+03$	$2.1847E + 05$	1.4217E+04	$5.0007E + 03$	$3.9643E+03$
	Rank	6	$\mathbf{3}$	$7\phantom{.0}$	5	4	9	8	$\overline{2}$	1
	Mean	$3.0198E + 06$	$3.6023E + 05$	2.3943E+07	3.3790E+05	4.8637E+05	$4.3833E+10$	8.7692E+09	2.7390E+04	$9.9690E + 04$
	Std	$5.6612E + 05$	2.0417E+05	1.1861E+07	$2.1903E + 05$	$2.6730E + 05$	4.1187E+09	2.9267E+09	1.9346E+04	$4.0134E + 04$
	<b>Best</b>	$1.8714E + 06$	$1.2271E+05$	8.0270E+06	6.3376E+04	$1.5702E + 05$	$3.0248E+10$	$5.2394E+09$	8.3717E+03	4.7054E+04
	Rank	6	4	$\tau$	3	5	9	8	1	2
	Total Rank	- 146	149	171	109	108	261	227	93	41
	Final Rank	5	6	$\tau$	4	3	9	8	2	1

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				<b>TABLE VIII</b>	MEAN VALUES OF WILCOXON SIGNED RANK TEST ON CEC2017 BENCHMARK FUNCTIONS.				
E HGSO			50		Dimension 100				
VS	$p$ -Value	$R+$	$R-$	$+/-/$	$p$ -Value	$R+$	$R-$	$+/-/$	
<b>TS22</b>	6.82E-03	54.72	410.28	26/2/1	9.20E-06	26.66	438.34	28/0/1	
<b>HBA</b>	4.57E-02	122.00	343.00	24/3/2	9.33E-04	42.31	422.69	27/0/2	
<b>FDA</b>	6.82E-03	54.72	410.28	26/2/1	9.20E-06	26.66	438.34	28/0/1	
<b>AHA</b>	2.21E-02	137.86	327.14	19/5/5	3.38E-03	74.90	390.10	26/1/2	
<sub>SO</sub>	$1.00E-01$	144.38	320.62	19/7/3	2.59E-03	59.17	405.83	26/1/2	
<b>BWO</b>	1.73E-06	0.00	465.00	29/0/0	2.49E-06	4.83	460.17	29/0/0	
<b>HGSO</b>	1.75E-06	1.03	463.97	29/0/0	3.23E-03	14.14	450.86	28/1/0	
<b>OHGSO</b>	1.51E-01	221.14	243.86	12/8/9	3.94E-02	169.62	295.38	19/5/5	
Mean Value	4.16E-02	91.98	373.02	23/3.4/2.6	6.19E-03	52.29	412.71	26.4/1/1.6	

TABLE VIII

SO 1.00E-01 144.38 320.62 19/7/3 2.59E-03<br>
BWO 1.75E-06 0.00 465.00 29/0/0 2.49E-06<br>
HGSO 1.75E-06 1.03 463.97 29/0/0 3.23E-03<br>
QHGSO 1.51E-01 221.14 243.86 12/8/9 3.94E-02 1<br>
Mean Value 4.16E-02 91.98 373.02 23/3.4/2.6 6. BWO 1.73E-06 0.00 465.00 29/0/0 2.49E-06 4.83<br>
HGSO 1.75E-06 1.03 463.97 29/0/0 3.23E-03 14.14<br>
QHGSO 1.51E-01 221.14 243.86 12/8/9 3.94E-02 169.62<br>
Mean Value 4.16E-02 91.98 373.02 23/3.42.6 6.19E-03 52.29<br>
According to t HGSO 1.75E-06 1.03 463.97 29/0/0 3.23E-03 14.14<br>
QHGSO 1.51E-01 221.14 243.86 12/8/9 3.94E-02 169.62<br>
Mean Value 4.16E-02 91.98 373.02 23/3.4/2.6 6.19E-03 52.29<br>
According to the data presented in Tables IV and V, the Feat QHGSO 1.51E-01 221.14 2<br>
Mean Value 4.16E-02 91.98 3<br>
Theory of the data presented in Tables IV<br>
E\_HGSO demonstrated superior performand<br>
dimension of 50, the E\_HGSO achieved the b<br>
16 out of the tested functions, and the Mean Value  $4.16E-02$   $91.98$   $373.02$   $23/3.4/2.6$   $6.19E-03$   $52.29$ <br>According to the data presented in Tables IV and V, the Feature selection is an im<br>HGSO demonstrated superior performance. For the classification, reg The main value of the data presented in Tables IV and V, the<br>
E-HGSO demonstrated superior performance. For the<br>
E-HGSO demonstrated superior performance. For the<br>
16 out of the tested functions, and the second-best resul According to the data presented in Tables IV and V, the<br>
E\_HGSO demonstrated superior performance. For the<br>
classification, regression, and of<br>
dimension of 50, the E\_HGSO achieved the best results in<br>
as it helps to avoi According to the data presented in 1 ables IV and V, the<br>
E-HGSO demonstrated superior performance. For the classification, regression, and<br>
dimension of 50, the E-HGSO achieved the best results in as it helps to avoid the E\_HOSO demonstrated superior performance. For the classistication, regression, and<br>
dimension of 50, the E\_HGSO achieved the best result in 8 and inconsistent features on n<br>
other functions. For the dimension of 100, the

dependent of the test of comparison of 30, the E-HOSO achieved the best result in 8 at ineps to avoid the accord-best comparison of 100, the E\_HGSO was combinatorical optimized the best performer in 22 functions and the se 16 out of me resident unconsolations, and the second-obset sesual in 8 and inconsistent leatures on meta-<br>the functions. For the dimension of 100, the E\_HGSO was combinatorial optimization<br>the best proformer in 22 function other functions. For the dimension of 100, the E\_HGSO was<br>
the best performer in 22 functions and the second-best in 6<br>
through methods of the E\_HGSO at the higher dimension. Importantly, the<br>
E\_HGSO exhibited the best ove best performare in 22 tunctions and the second-best in 6<br>
employed metanceusions. This indicates an even greater overall advantage<br>
relevant features, with the aimstractions.<br>
The EHGSO exhibited the best overall results a The E-HGSO at the higher dimensions. This matted is the higher dimension. Importantly, the the endity of high-dimension of the E-HGSO exhibited the best overall results across both employing a wide range of da problem dime of the E-HOSO at the migher dimension. Importantly, the the quality of nigh-dimensions evently are problem dimensions. A visual comparison of the above algorithms in 50 and the methods tend to the comparison of the above a E\_HOSO exinoted the best overall results across both employing a wate range of data<br>
roblems dimensions.<br>
The much dimensions is given in Table VI. E\_HGSO always these methods tend to ustiff<br>
100 dimensions is given in Ta

proonen amensions.<br>
A visual comparison of the above algorithms in 50 and<br>
100 dimensions is given in Table VI. E HGSO always study, we propose a nev<br>
significantly outperforms the other algorithms and there is<br>
to improve A visual comparison of the above algorithms in 5 using throbens is a to the significantly outperforms the other algorithms and there is significantly improved the performance of HGSO always study, we propose a features usi 100 dimensions is given in 1able VI. E\_HGSO always<br>
singificantly outpreforms the other algorithms and three is to improve classification accur<br>
singificantly improved the performance of HGSO. The The choice of feature sel signincantly outperforms the other algorithms and there is to improve classification<br>
no worst result, indicating that the improved strategy has features using the HGSO.<br>
significantly improved the performance of HGSO. The no worst result, indicating that the improved strategy has<br>
significantly improved the performance of HGSO. The choice of feature sells<br>
or expectific proposed strategy<br>
in the E\_HGSO algorithm is more helpful in improving signincantly improved the performance of HOSO. The the choice of reactive selections in the E\_HGSO algorithm is more helpful in improving the computational resources aver<br>formance of HGSO in high dimensional space. genera results of comparative tests show that the proposed strategy<br>
in the E\_HGSO algorithm is more helpful in improving the<br>
proposed strategy<br>
proving the computational resources awe<br>
proformance of HGSO in high dimensional sp in the E\_HGSO algorithm is more nelptul in improving the<br>
performance of HGSO in high dimensional space.<br>
Table VII shows the results of the Friedman test for all the<br>
algorithms. The p-values for 50 and 100 dimensions are romance of HOSO in high dimensional space.<br>
Table VII shows the results of the Friedman test for all the exact interactions. Wrap<br>
gorithms. The p-values for 50 and 100 dimensions are explore the feature space at<br>
3399e-34 Table VII all p-values are found the reference interventions. Wrap<br>
algorithms. The p-values for 50 and 100 dimensions are explore the feature space are applicant. The average rank of the Friedman<br>
T.4399e-34 and 1.0728e-3 argoritms. Ine p-values for 50 and 100 dimensions are<br>
7.4399e-34 and 1.0728e-32, respectively. Since the p-values feature space and<br>
are much less than 0.05, we consider the statistical results to methods offer a balance Considerable advantage of E\_HGSO algorithm in both 50-<br>
are much statistical results of the Statistical results of the Statistical results of the Statistical results these that of the E\_HGSO is 1.7241 and 1.4138, respecti and 10.03, we consider the statistical results of methods of the model train<br>
be statistically significant. The average rank of the Friedman<br>
be statistically significant which is better than the other compared algorithms. be statistically significant I ne average rank of the Firedman<br>
tection winnin the model trat<br>
test for the E\_HGSO is 1.7241 and 14.4138, respectively,<br>
which is better than the other compared algorithms. In<br>
data set are

test for the E\_HGSO is 1./241 and 1.4138, respectively, when solved<br>which is better than the other compared algorithms. In data set are<br>contrast, the mean ranks of the HGSO algorithm are 8.0000 features are<br>and 7.8276, res The mean ranks of the HGSO algorithm are 8.0000<br>
Teatures are released and ranks of the HGSO algorithm. This suggests that the irrelevant features in<br>
e. of the EHGSO algorithm. This suggests that the irrelevant features poposed enhancement strategy greatly improves the larger content. Selectir<br>formance of the original HGSO algorithm.<br>In Table VIII, all p-values are found to be less than 0.05, process that aims to fin<br>gegesting that the st Proformance of the original HGSO algorithm.<br>
In Table VIII, all p-values are found to be less than 0.05,<br>
reproformance of the Wilcoxon signed rank test demonstrate a<br>
results of the Wilcoxon signed rank test demonstrate a In Table VIII, all p-values are found to be less than 0.05,<br>
suggesting that the statistical results are significant. The<br>
considerable advantage of E-HGSO algorithm in both 50-<br>
considerable advantage of E-HGSO algorithm

# SELECTION of 2N - 1.

suggesting that the statistical results are significant. The<br>
results of the Wilcoxon signed rank test demonstrate a<br>
considerable advantage of E\_HGSO algorithm in both 50-<br>
and 100-dimensional test functions. Thus, it can results of the Wilcoxon signed rank test demonstrate a<br>
considerable advantage of E\_HGSO algorithm in both 50-<br>
ceatures are unselected.<br>
and 100-dimensional test functions. Thus, it can be<br>
concluded that E\_HGSO signific considerable advantage of E-HGSO algorithm in both 50-<br>
and 100-dimensional test functions. Thus, it can be<br>
concluded that E-HGSO significantly outperforms the<br>
comparison algorithms, with statistical significance.<br>
W. T and 100-dimensional test functions. Thus, it can be<br>
concluded that E\_HGSO significantly outperforms the<br>
comparison algorithms, with statistical significance.<br>
V. APPLICATION OF E\_HGSO FOR FEATURE<br>
SELECTION<br>
SELECTION<br> concluded that E\_HGSO significantly outperforms the<br>comparison algorithms, with statistical significance.<br>V. APPLICATION OF E\_HGSO FOR FEATURE<br>SELECTION<br>Feature selection is also called Feature Subset Selection<br>(FS) [42].

9.20E-06 26.66 438.34 28/0/1<br>
3.38E-03 74.90 390.10 26/1/2<br>
2.59E-03 59.17 405.83 26/1/2<br>
2.49E-06 4.83 460.17 29/00<br>
3.23E-03 14.14 450.86 28/1/0<br>
3.94E-02 169.62 295.38 19/5/5<br>
6.19E-03 52.29 412.71 26.4/1/1.6<br>
Feature 3.38E-03 74.90 390.10  $26/1/2$ <br>
2.59E-03 59.17 405.83  $26/1/2$ <br>
2.49E-06 4.83 460.17  $29/00$ <br>
3.23E-03 14.14 450.86  $28/1/0$ <br>
3.94E-02 169.62  $295.38$  19/5/5<br>
6.19E-03 52.29 412.71  $26.4/1/1.6$ <br>
Feature selection is an im 2.59E-03 59.17 405.83  $261/2$ <br>
2.49E-06 4.83 460.17  $29/0/0$ <br>
3.23E-03 14.14 450.86  $28/1/0$ <br>
3.94E-02 169.62  $295.38$  19/5/5<br>
6.19E-03 52.29 412.71  $26.4/1/1.6$ <br>
Feature selection is an important pre-processing step in<br> 2.49E-06 4.83 460.17 29/00<br>3.23E-03 14.14 450.86 28/1/0<br>3.94E-02 169.62 295.38 19/5/5<br>6 6.19E-03 52.29 412.71 26.4/1/1.6<br>Feature selection is an important pre-processing step in<br>classification, regression, and other data 3.23E-03 14.14 450.86 28/1/0<br>3.94E-02 169.62 295.38 19/5/5<br>6 6.19E-03 52.29 412.71 26.4/1/1.6<br>Feature selection is an important pre-processing step in<br>classification, regression, and other data mining applications,<br>as it 3.94E-02 169.62 295.38 19/5/5<br>
6.19E-03 52.29 412.71 26.4/1/1.6<br>
Feature selection is an important pre-processing step in<br>
classification, regression, and other data mining applications,<br>
as it helps to avoid the adverse  $6.19E-03$   $52.29$   $412.71$   $26.4/1/1.6$ <br>
Feature selection is an important pre-processing step in<br>
classification, regression, and other data mining applications,<br>
as it helps to avoid the adverse effects of noisy, misle Feature selection is an important pre-processing step in<br>classification, regression, and other data mining applications,<br>as it helps to avoid the adverse effects of noisy, misleading,<br>and inconsistent features on model pe Feature selection is an important pre-processing step in<br>classification, regression, and other data mining applications,<br>as it helps to avoid the adverse effects of noisy, misleading,<br>and inconsistent features on model per Fracture selection is an important pre-processing step<br>classification, regression, and other data mining applicati<br>as it helps to avoid the adverse effects of noisy, misleadi<br>and inconsistent features on model performance. issimication, regression, and other data mining applications,<br>it helps to avoid the adverse effects of noisy, misleading,<br>misloarding of inconsistent features on model performance. As a global<br>mohinatorial optimization pro as it neips to avoid the adverse effects of noisy, misleading,<br>and inconsistent features on model performance. As a global<br>combinatorial optimization problem, researchers have<br>employed metaleuristic algorithms to select th and mconsistent leatures on model performance. As a globat<br>combinatorial optimization problem, researchers have<br>employed metaheuristic algorithms to select the most<br>relevant features, with the aim of simplifying and improv combinatorial optimization problem, researchers have<br>employed metaheuristic algorithms to select the most<br>relevant features, with the aim of simplifying and improving<br>the quality of high-dimensional datasets. However, when

employed metaneuristic algorithms to select the most<br>relevant features, with the aim of simplifying and improving<br>the quality of high-dimensional datasets. However, when<br>employing a wide range of datasets with large featur relevant reatures, with the aim of simplifying and improving<br>the quality of high-dimensional datasets. However, when<br>employing a wide range of datasets with large feature sizes,<br>these methods tend to suffer from local opti the quality of mgn-dimensional datasets. However, when<br>employing a wide range of datasets with large feature sizes,<br>these methods tend to suffer from local optimization<br>problems due to the considerable solution space. In t employing a wide range or datasets with large reature sizes,<br>these methods tend to suffer from local optimization<br>problems due to the considerable solution space. In this<br>study, we propose a new dimensionality reduction ap mese mentoas tend to surier from local optimization<br>problems due to the considerable solution space. In this<br>study, we propose a new dimensionality reduction approach<br>to improve classification accuracy by selecting signifi bolems due to the considerable solution space. In this<br>idy, we propose a new dimensionality reduction approach<br>improve classification accuracy by selecting significant<br>tures using the HGSO.<br>The choice of feature selection study, we propose a new dimensionality reduction approach<br>to improve classification accuracy by selecting significant<br>features using the HGSO.<br>The choice of feature selection method depends on the<br>specific problem, the cha from the contraction accuracy by selecting signineant<br>features using the HGSO.<br>The choice of feature selection method depends on the<br>specific problem, the characteristics of the dataset, and the<br>computational resources ava reatures using the HOSO.<br>The choice of feature selection method depends on the<br>specific problem, the characteristics of the dataset, and the<br>computational resources available. Filter methods are<br>generally faster and simple

Ine choice of reature selection method depends on the<br>specific problem, the characteristics of the dataset, and the<br>computational resources available. Filter methods are<br>generally faster and simpler, but may not capture co specific problem, the characteristics of the dataset, and the computational resources available. Filter methods are complex feature interactions. Wrapper methods can effectively explore the feature invarianty features, but computational resources available. Filter methods are<br>generally faster and simpler, but may not capture complex<br>feature interactions. Wrapper methods can effectively<br>explore the feature space and identify the most relevant generally laster and simpler, but may not capture complex<br>feature interactions. Wrapper methods can effectively<br>explore the feature space and identify the most relevant<br>features, but can be computationally intensive. Embed reautre mieractions. Wrapper methods can eliectively<br>explore the feature space and identify the most relevant<br>features, but can be computationally intensive. Embedded<br>methods offer a balance between the two, integrating fe explore the reature space and identity the most relevant<br>features, but can be computationally intensive. Embedded<br>methods offer a balance between the two, integrating feature<br>selection within the model training process.<br>Wh reatures, but can be computationally intensive. E<br>methods offer a balance between the two, integratir<br>selection within the model training process.<br>When solving classification problems, not all fea<br>data set are relevant, an entions of the model training process.<br>
When solving classification problems, not all features in a<br>
When solving classification problems, not all features in a<br>
ta set are relevant, and often only a small number of<br>
tatur selection within the model training process.<br>
When solving classification problems, not all features in a<br>
data set are relevant, and often only a small number of<br>
features are relevant and can help determine the<br>
classifi when solving classification problems, not all reatures in a<br>data set are relevant, and often only a small number of<br>features are relevant and can help determine the<br>classification goal. In the era of big data, these worthl data set are relevant, and otien only a small number of<br>
features are relevant and can help determine the<br>
classification goal. In the era of big data, these worthless<br>
irrelevant features present in huge datasets usually reatures are relevant and can neip determine the<br>classification goal. In the era of big data, these worthless<br>irrelevant features present in huge datasets usually take up a<br>subst of features is the best<br>solution to the abo classification goal. In the era of big data, the irrelevant features present in huge datasets usu larger content. Selecting a subset of feature solution to the above problems. Feature sprocess that aims to find a subset o elevant leatures present in nige datasets usuarly take up a<br>ger content. Selecting a subset of features is the best<br>dution to the above problems. Feature selection is a<br>occess that aims to find a subset of relevant feature

arger content. Selecting a stubset of leatures is the best<br>solution to the above problems. Feature selection is a<br>process that aims to find a subset of relevant features from<br>the original set. It can be seen that the subse

solution to the above problems. Feature selection is a<br>process that aims to find a subset of relevant features from<br>the original set. It can be seen that the subset of relevant<br>features contains all the selected features a process inal alms to that a subset of retevant leatures from<br>the original set. It can be seen that the subset of relevant<br>features contains all the selected features and the remaining<br>features are unselected.<br>Therefore, fo the original set. It can be seen that the subset of relevant<br>features contains all the selected features and the remaining<br>features are unselected.<br>Therefore, for each feature, there are two possibilities, "1"<br>for selected reatures contains all the selected reatures and the remaining<br>features are unselected.<br>Therefore, for each feature, there are two possibilities, "1"<br>for selected feature and "0" for unselected feature. The<br>number of featur reatures are unselected.<br>
Therefore, for each feature, there are two possibilities, "1"<br>
for selected feature and "0" for unselected feature. The<br>
number of feature subsets is 2N - 1 when the feature space is<br>
N. This prob Fraction problem and "0" for unselected feature. Then the mumber of feature and "0" for unselected feature. The number of feature subsets is  $2N - 1$  when the feature space is  $N$ . This problem has long ben shown to be NPproblem.

**Engineering Letters**<br>Objective 1: Feature subset size. Based on the number of<br>" in the statistics set, we can get the number of currently<br>lected features, so the first measure is shown in Equation<br>: **Engineering Letters**<br>
Objective 1: Feature subset size. Based on the number of<br>
"1" in the statistics set, we can get the number of currently<br>
selected features, so the first measure is shown in Equation<br>
18: **Engineering Letters**<br>
Objective 1: Feature subset size. Based on the number of<br>
"1" in the statistics set, we can get the number of currently<br>
selected features, so the first measure is shown in Equation *fitness* =<br>
18: 18: Objective 1: Feature subset size. Based on the number of<br>
"1" in the statistics set, we can get the number of currently<br>
selected features, so the first measure is shown in Equation<br>
18:<br>  $f_1(X) = \sum_{1}^{D} x_i$  (18)<br>
Where  $\$ Objective 1: Feature subset size. Based on the number of<br>
"1" in the statistics set, we can get the number of currently<br>
selected features, so the first measure is shown in Equation<br>  $f_1(X) = \sum_{1}^{D} x_i$  (18) Where  $\Delta_R(D)$ 

$$
f_1(X) = \sum_{1}^{D} x_i
$$
 (18)

$$
f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}
$$
 (19)

"1" in the statistics set, we can get the number of curr<br>selected features, so the first measure is shown in Equ<br>18:<br> $f_1(X) = \sum_{1}^{D} x_i$ <br> $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$ <br>Where Nerr denotes the number of classification erro is external the first measure is shown in Equation<br>  $f_1(X) = \sum_{1}^{D} x_i$  (18) Where  $\Delta_R(D)$  denotes the number<br>  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19) E\_HGSO algorithm,<br>
here Nerr denotes the number of classification errors; 18:<br>  $f_1(X) = \sum_{1}^{D} x_i$  (18) Where  $\Delta_R(D)$  denotes the<br>
Nearest Neighbours (KN)<br>
denotes the number of  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19) E\_HGSO algorithm, |*Tz*| de<br>
where *Nerr* denotes the number of classification e  $f_1(X) = \sum_{1}^{D} x_i$  (18) Where  $\Delta_R(D)$  denotes the number<br>  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19) E\_HGSO algorithm,<br>
Where Nerr denotes the number of classification errors; Nall contained in the curr<br>
where Nerr denotes the  $f_1(X) = \sum_{1}^{D} x_i$  (18) Where  $\Delta_R(D)$  denotes the<br>
Nearest Neighbours (KN<br>  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19) E\_HGSO algorithms, |<br>
Where Nerr denotes the number of classification errors; Nall<br>
where Nerr denotes the n  $f_1(X) = \sum_{1} x_i$  (18)<br>  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19)<br>
Where *Nerr* denotes the number of classification errors; *Nall*<br>
denotes the number of all classified samples. *n* denotes the<br>
cross-validation Parameters.<br>
T  $f_2(X) = \frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$ <br>here *Nerr* denotes the number of classification ernotes the number of all classified samples. *n* de<br>oss-validation Parameters.<br>The use of simple and easy-to-implement clas<br>gorithms in wr

 $J_2(A) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{Nall}$  contained in the current datas<br>
where Nerr denotes the number of classification errors; Nall<br>
contained in the current datas<br>
where Nerr denotes the number of all classified samples. *n* Where Nerr denotes the number of classification errors; Nall<br>
to the classification error rate<br>
denotes the number of all classified samples. *n* denotes the<br>
cross-validation Parameters.<br>
The use of simple and easy-to-im Where *Nerr* denotes the number of classification errors; *Nall*  $\Psi$  =1.<br>
denotes the number of all classified samples. *n* denotes the<br>
cross-validation Parameters.<br>
The capacity of the use of simple and easy-to-impleme where *Nerr* denotes the number of classification errors; *Nall*  $\epsilon$  *R. Data sets and pecons-validation Parameters.* The use of simple and easy-to-implement classification the capacity of the capacity of the use of simp denotes the number of all cassined samples. *n* denotes the<br>
cross-validation Parameters.<br>
The capacity of the EHG<br>
cross-validation Parameters.<br>
The use of simple and easy-to-implement classification<br>
of feature selectio Cross-vantation praimeters.<br>
The use of simple and easy-to-implement classification<br>
and algorithms in wrapping methods can result in a good subset<br>
on 8 standard datasets obt<br>
of features that are also applicable to comp The use of simple and easy-to-implement classification<br>
algorithms in wrapping methods can result in a good subset<br>
of features that are also applicable to complex classification<br>
of features that are also applicable to c algorithms in wrapping memots can result in a good subset<br>of features that are also applicable to complex classification<br>algorithms. Therefore, this paper introduces the *K-NN* are presented in Table IX. For<br>method as a c of leatures that are also applicable to complex classification<br>
algorithms. Therefore, this paper introduces the *K-NN* are presented in Table IX. For<br>
method as a classifice [44].<br> *A. Model building*<br>
from the perspecti algorithms. Interfore, this paper introduces the  $A-N/N$  are presented an another and the mange [0, 1]. S<br>
method as a classifier [44].<br>
From the perspective of intelligent optimization, the divided into training and tes<br>
f memon as a classinier particularly and the material scaled to the range [0, 1].<br>
And *a louiding* scaled to the range [0, 1].<br>
From the perspective of intelligent optimization, the divided into training and<br>
feature selec A. Model building to the light optimization, the simulation training in From the perspective of intelligent optimization, the divided into training if eature selection problem is to obtain a solution that minimises the co From the perspective of intelligent optimization, the<br>
feature selection problem is to obtain a solution that<br>
minimizies the subset of features and maximises the<br>
evolution for a family of solution vectors whose dimensio reature seection problem is to obtain a solution that constant we<br>classification accuracy through the process of population<br>classification accuracy through the process of population<br> $\text{L}$  Nearest Neighbors (KNN) c<br>classi minimises the subset of leatures and maxi-<br>classification accuracy through the process of<br>evolution for a family of solution vectors whose c<br>are the number of features of the problem, repres<br>and 1. When solving the feature

$$
fitness = \xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|} \tag{20}
$$

**Engineering Letters**<br>
bbset size. Based on the number of<br>
ve can get the number of currently<br>
dirst measure is shown in Equation<br>
(*X*) =  $\sum_{1}^{D} x_i$  (18)<br>
(18)<br>
(18)<br>
(18)<br>
(19)<br>  $\frac{1}{n} \sum_{1}^{n} \frac{Nerr}{Nall}$  (19)<br>  $\frac{1}{$ Where  $\Delta_R(D)$  denotes the classification error rate using K *<sup>i</sup> f X x* (18) denotes the number of feature subsets selected by the E HGSO algorithm,  $|T_z|$  denotes the total number of features **Engineering Letters**<br>
Engineering Letters<br>
e subset size. Based on the number of<br>
i, we can get the number of currently<br>
in Equation<br>  $f_1(X) = \sum_{i=1}^{D} x_i$  (18)<br>
Where  $\Delta_R(D)$  denotes the classific<br>
denotes the number of **Engineering Letters**<br>
are subset size. Based on the number of<br>
ret, we can get the number of currently<br>
the first measure is shown in Equation<br>  $f_1(X) = \sum_{i=1}^{D} x_i$  (18)<br>
Merre  $\Delta_R(D)$  denotes the classis<br>  $f_2(X) = \frac{1}{n}$ **Engineering Letters**<br>
set size. Based on the number of<br>
can get the number of currently<br>
in measure is shown in Equation<br>  $Y = \sum_{i=1}^{p} x_i$  (18) Where  $\Delta_R(D)$  denotes the classification error rate using K<br>  $Y = \sum_{i=1}^{p} x_i$  $(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>sification error rate using K<br>classification error rate, |Y|<br>re subsets selected by the<br>st the total number of features<br>t. and  $\xi$  is a parameter related  $_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
assification error rate using K<br>
classification error rate, |*Y*|<br>
ture subsets selected by the<br>
tes the total number of features<br>
et, and  $\zeta$  is a parameter related<br>
whichts  $\zeta$  *W* = [0, *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
denotes the classification error rate using K<br>
thbours (KNN) classification error rate, |Y|<br>
number of feature subsets selected by the<br>
prithm, |Tz| denotes the total number o =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
s the classification error rate using K<br>
(KNN) classification error rate, |Y|<br>
of feature subsets selected by the Frances  $\int f$  *f iness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |*Y*|<br>
denotes the number of feature subsets sel Francestockey  $\int$  *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |*Y*|<br>
denotes the number of feature subset **Example 18 (A)**  $\text{fitness} = \xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |Y|<br>
denotes the number of feature subsets selected Fitness =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |*Y*|<br>
denotes the number of feature subsets selected by the<br>
E\_ *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |Y|<br>
denotes the number of feature subsets selected by the<br>
E\_ *fitness* = ξ ⋅ Δ<sub>R</sub>(D) + Ψ ⋅  $\frac{|Y|}{|T_z|}$  (20)<br>
Where Δ<sub>R</sub>(D) denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |Y|<br>
denotes the number of feature subsets selected by t *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |*Y*|<br>
denotes the number of feature subsets selected by the<br> *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{|Y|}{|T_Z|}$  (20)<br>
here  $\Delta_R(D)$  denotes the classification error rate using K<br>
carest Neighbours (KNN) classification error rate, |*Y*|<br>
notes the number of feature subsets selected by the<br>
HGSO *fitness* =  $\xi \cdot \Delta_R(D) + \psi \cdot \frac{1}{|T_Z|}$  (20)<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |Y|<br>
denotes the number of feature subsets selected by the<br>
E\_H <sup>1</sup>  $I_Z$  |<br>
Where  $\Delta_R(D)$  denotes the classification error rate using K<br>
Nearest Neighbours (KNN) classification error rate, |*Y*|<br>
denotes the number of feature subsets selected by the<br>
E\_HGSO algorithm, |*Tz*| denotes t

 $f_2(X) = \frac{1}{n} \sum_{i=1}^{n} \frac{Nerr}{Nall}$  (19) E HGSO algorithm,  $|Tz|$  denot<br>
to the classification errors; Nall the current datase<br>
to the classification error at the current datase<br>
to the classification error at the current Where  $\Delta_R(D)$  denotes the classification error rate using K<br>Nearest Neighbours (KNN) classification error rate, |*Y*|<br>denotes the number of feature subsets selected by the<br>E\_HGSO algorithm, |*Tz*| denotes the total number Where  $\Delta_R(D)$  denotes the classification error rate using K<br>Nearest Neighbours (KNN) classification error rate, |*Y*|<br>denotes the number of feature subsets selected by the<br>E\_HGSO algorithm, |*Tz*| denotes the total number Nearest Neighbours (KNN) classification error rate, |*Y*|<br>denotes the number of feature subsets selected by the<br>E\_HGSO algorithm, |*Tz*| denotes the total number of features<br>contained in the current dataset, and  $\xi$  is a SCREE TRESS ALTER THE SCREET NET THE ENCORDING THE ENGS of the number of feature subsets selected by the E-HGSO algorithm,  $|Tz|$  denotes the total number of features contained in the current dataset, and  $\zeta$  is a param denotes the miniber of readile slosses selected by the E-HGSO algorithm,  $|Tz|$  denotes the total number of features contained in the current dataset, and  $\xi$  is a parameter related to the classification error rate weigh  $E_$ INGSO algorium,  $|Iz|$  denotes the total number of reatures<br>contained in the current dataset, and  $\xi$  is a parameter related<br>to the classification error rate weights,  $\xi$ ,  $\Psi \in [0, 1]$ , and  $\xi +$ <br> $\Psi = 1$ .<br>*B. Data s* contained in the curient dataset, and  $\zeta$  is a parameter related<br>to the classification error rate weights,  $\xi$ ,  $\Psi \in [0, 1]$ , and  $\xi + \Psi = 1$ .<br>B. Data sets and performance metrics<br>The capacity of the E\_HGSO algorithm to In this case, we will continue to use the same 8 algorithm of the same as TD and a meta-<br>In the capacity of the E-HGSO algorithm to perform<br>The capacity of the E-HGSO algorithm to perform<br>ature selection was evaluated by  $F=1$ .<br> *B. Data sets and performance metrics*<br>
The capacity of the E\_HGSO algorithm to perform<br>
feature selection was evaluated by conducting experiments<br>
on 8 standard datasets obtained from the UCI Machine<br>
Learning Re B. Data sets ana performance metrics<br>The capacity of the E\_HGSO algorithm to perform<br>feature selection was evaluated by conducting experiments<br>form the UCI Machine<br>Dearning Repository. The specific details of these datase Ine capacity of the E\_HGSO algorithm to perform<br>feature selection was evaluated by conducting experiments<br>on 8 standard datasets obtained from the UCI Machine<br>Learning Repository. The specific details of these dataset<br>sar reautre setection was evaluated by conducting experiments<br>on 8 standard datasets obtained from the UCI Machine<br>Learning Repository. The specific details of these dataset<br>underwent max-min normalization, whereby the data we

on 8 standard datasets obtained from the UCI Machine<br>Learning Repository. The specific details of these datasets<br>are presented in Table IX. For the evaluation, each dataset<br>underwent max-min normalization, whereby the data Learning Repository. The specific details of these datasets<br>are presented in Table IX. For the evaluation, each dataset<br>underwent max-min normalization, whereby the data were<br>scaled to the range [0, 1]. Subsequently, each are presented in Table IX. For the evaluation, each dataset<br>underwent max-min normalization, whereby the data were<br>scaled to the range [0, 1]. Subsequently, each dataset was<br>divided into training and test subsets. The feat underwent max-min normailzation, whereby the data were<br>scaled to the range [0, 1]. Subsequently, each dataset was<br>divided into training and test subsets. The feature subsets<br>botaned for each individual were then classified scaled to the range [0, 1]. Subsequently, each dataset was<br>divided into training and test subsets. The feature subsets<br>obtained for each individual were then classified using the<br>K-Nearest Neighbors (KNN) classifier.<br>In th divided mot training and test subsets. The leadure subsets<br>obtained for each individual were then classified using the<br>K-Nearest Neighbors (KNN) classifier.<br>In this case, we will continue to use the same 8 algorithms<br>as t obtained for each mutvidual were then classified using the K-Nearest Neighbors (KNN) classifier.<br>In this case, we will continue to use the same 8 algorithms<br>as the comparative algorithms, with all their parameters set<br>the K-Nearest Neignbors (KNN) classiner.<br>
In this case, we will continue to use the same 8 algorithms<br>
as the comparative algorithms, with all their parameters set<br>
the same as in the previous experiments. The E\_HGSO<br>
algorit In this case, we will continue to use the same 8 algorithms<br>as the comparative algorithms, with all their parameters set<br>the same as in the previous experiments. The E\_HGSO<br>algorithm is initialized randomly, with a popula





[41]:

$$
AvgAcc = \frac{1}{Q} \sum_{i=1}^{Q} Acc_i
$$
 (21) large the value  
unstable. The sta

<sup>7</sup><br>
<sup>8</sup> cylinder-bands <sup>512</sup><br>
Average accuracy: The average accuracy is the average Where *fitness<sub>i</sub>* denotes the option of the classification accuracies of the optimization algorithm in the *i*th run.<br>
when performing **between runder of the classification** accuracy: The average accuracy is the average Where *fitness<sub>i</sub>* denoted of the classification accuracies of the optimization algorithm in the *i*th run.<br>
When performing feature sel **Example accuracy:** The average accuracy is the average Where *fitness<sub>i</sub>* denotes the optimization accuracies of the optimization algorithm in the *i*th run.<br>
When performing feature selection and is defined as follows **Average accuracy:** The average accuracy is the average Where *fitness<sub>i</sub>* denotes the open of the classification accuracies of the optimization algorithm in the *i*th run.<br>
When performing feature selection and is define **Example and Solution** Average accuracy: The average accuracy is the average where *Jithesis* denotes the optimization accuracies of the optimization algorithm in the *kh* in the KNN classification and is defined as follo of the classification accuraces of the optimization algorithm<br>
when performing feature selection and is defined as follows<br>
magnitude of volatility of the standard deviation of fitne<br>
magnitude of volatility of the standa follows: Where *Q* denotes the number of times the algorithm has<br>
been run, *Acc<sub>i</sub>* denotes the optimal solution of classification<br>
accuracy obtained by the *i*th run of the algorithm, and the<br>
larger the value of *k* in the KNN where  $\mu$ <sub>sed</sub> is the number of descriptors, and *ACC*<sub>cv5</sub> is the precision of the other algorithm, and the state of *k* in the KNN classifier was set to 5 during the Table X presents the results experimental analysis. been run, *Acci* denotes the optimal solution of class<br>accuracy obtained by the *i*th run of the algorithm,<br>larger the value of *AvgAcc*, the better the classificat<br>value of *k* in the KNN classifier was set to 5 du<br>exper

$$
fitness = \frac{0.95}{ACCcv5} + \frac{0.05 \times n_{sel}}{N_{tot}}
$$
 (22) terms of fitness values, a  
algorithm performance. Up  
evident that the E HGSO s

Experimental analysis. So the adaptation is expressed as<br>
follows:<br>
follows:<br>
follows:<br>
for the mast and standard devotional sumber of eaching the mean and standard devotional<br>
optimal value. The best results in all eight fiteness =  $\frac{0.95}{\Lambda C C c v 5} + \frac{0.05 \times n_{sel}}{N_{tot}}$  (22) terms optima<br>
where  $n_{sel}$  is the number of selected descriptors,  $N_{tot}$  is the the best<br>
total number of descriptors, and  $\Lambda C C_{c v 5}$  is the precision of the beh<br>
t

$$
AvgSize = \frac{1}{Q} \sum_{i=1}^{Q} \frac{size_i}{D}
$$
 (23) E\_HGSO not  
also exhibits  
results. This

total number of descriptors, and  $AC_{\text{co5}}$  is the precision of<br>the five-fold cross-validation.<br>the five-fold cross-validation.<br>of feature selection number: The average number<br>of feature selections is the average of the n the ive-told cross-validation.<br> **Average from Average number:** The average number<br>
of feature selections is the average of the number of features<br>
selected by the optimal solution obtained in Q runs of the<br>
algorithm over **Average teature selection number:** The average number<br>
of features of the number of features<br>
selected by the optimal solution obtained in Q runs of the<br>
algorithm over the total number of selectures in the dataset,<br>
whi of reature selections is the average of the number of leatures<br>
selected by the orginal solution obtained in Q runs of the<br>
algorithm over the total number of features in the dataset,<br>
undependently ten times of<br>
which is selected by the optimal solution obtained in *Q* runs of the<br>algorithm over the total number of features in the dataset,<br>which is expressed as follows Eq 23:<br>selection is the probability to the data. From the data in the algorithm over the total number of teatures in<br>which is expressed as follows Eq 23:<br> $AvgSize = \frac{1}{Q} \sum_{i=1}^{Q} \frac{size_i}{D}$ <br>Where size<sub>i</sub> denotes the number of features sele<br>optimal solution in the *i*th run, *D* is the total<br>feat **AvgSize** =  $\frac{1}{Q}$  =  $\frac{1}{\sqrt{Q}} \sum_{i=1}^{Q} \frac{size_i}{D}$  =  $\frac{1}{\sqrt{Q}} \sum_{i=1}^{Q} \frac{size_i}{D}$  =  $\frac{1}{\sqrt{Q}} \sum_{i=1}^{Q} \frac{size_i}{D}$  = HGSO not only achieves his expected by the exact of the data. From the *i*m all solution in the *i AvgSize* =  $\frac{1}{Q} \sum_{i=1}^{Q} \frac{size_i}{D}$  (23) also exhibits fewer outliers his consistents in the original solution in the *ift* number of features selected by the E\_HGSO. The consistent his fewer outliers from the origina

algorithm.

$$
AvgAve = \frac{1}{Q} \sum_{i=1}^{Q} fitness_i
$$
 (24) Fig.6

569 32<br>
351 34<br>
208 60<br>
512 39<br>
Where *fitness<sub>i</sub>* denotes the optimal solution fitness obtained<br>
in the *i*th run.<br> **Standard deviation of fitness**: The variance indicates the<br>
magnitude of volatility of the solution, th Where *fitness<sub>i</sub>* denotes the optimal solution fitness obtained<br>in the *i*th run.<br>**Standard deviation of fitness:** The variance indicates the<br>magnitude of volatility of the solution, the smaller its value,<br>the more the a the *i*th run.<br> **Standard deviation of fitness:** The variance indicates the ganitude of volatility of the solution, the smaller its value,  $e$  more the algorithm can converge to the same value; the ger the value, the more

$$
AvgStd = \sqrt{\frac{1}{Q} \sum_{i=1}^{Q} (fitness_i - Ave)^2}
$$
 (25)

*fiteness ACCcv N* Example of  $Avg.$  and an or the agorithm over the telection of the selection of  $\lambda$  and  $\lambda$  an angle to value of *k* in the KNN classifier was set to 5 during the reachable X presents the experimental analysis. So the adaptation is expressed as a delight comparison all expressed to the mean and standard deptitions: selected by the optimal solution obtained in *<sup>Q</sup>* runs of the *C*  $\frac{Q}{4\pi i}$ <br>
the number of times the algorithm has<br>
tooks the opinual solution of classification<br>
by the fitti more that algorithm, and the<br> *size Avg Stal* =  $\sqrt{\frac{1}{Q}} \sum_{i=1}^{Q} (fitness_i - Ave_i^2)$ <br> *Avg Acc*, the better t **Example 1.1** and **and deviation of fitness:** The variance indicates the magnitude of volatility of the solution, the smaller its value, the more the algorithm can converge to the same value; the larger the value, the mor magnitude of volatility of the solution, the smaller its value,<br>the more the algorithm can converge to the same value; the<br>larger the value, the more the algorithm is volatile and<br>unstable. The standard deviation is defin the more the algorithm can converge to the same value; the<br>larger the value, the more the algorithm is volatile and<br>larger the value, the more the algorithm is volatile and<br>unstable. The standard deviation is defined as:<br> the mean environment of the E-HGSO algorithm is volatile and<br>larger the value, the more the algorithm is volatile and<br>unstable. The standard deviation is defined as:<br> $AvgStd = \sqrt{\frac{1}{Q} \sum_{i=1}^{Q} (fitness_i - Ave)^2}$  (25)<br>Where Ave denotes algorithm performance and exist of the results, the vertex states of the results.<br>
Where Ave denotes the average adaptation.<br>
Table X presents the results of the E\_HGSO algorithm<br>
and eight comparison algorithms for 8 dat *AvgStd* =  $\sqrt{\frac{1}{Q} \sum_{i=1}^{Q} (fitness_i - Ave)^2}$  (25)<br>Where *Ave* denotes the average adaptation.<br>Table X presents the results of the E\_HGSO algorithm<br>and eight comparison algorithms for 8 datasets, including<br>the mean and standar *AvgStd* =  $\sqrt{\frac{1}{Q} \sum_{i=1}^{Q} (fitness_i - Ave)^2}$  (25)<br>
Where *Ave* denotes the average adaptation.<br>
Table X presents the results of the E\_HGSO algorithm<br>
and eight comparison algorithms for 8 datasets, including<br>
the mean and sta  $AvgStd = \sqrt{\frac{1}{Q} \sum_{i=1}^{Q} (fitness_i - Ave)^2}$  (25)<br>
Where *Ave* denotes the average adaptation.<br>
Table X presents the results of the E\_HGSO algorithm<br>
and eight comparison algorithms for 8 datasets, including<br>
the mean and standard de The other algorithms.<br>
The other algorithm and eight comparison algorithms for 8 datasets, including<br>
the mean and standard deviation of the E-HGSO algorithm<br>
and eight comparison algorithms for 8 datasets, including<br>
the Where Ave denotes the average adaptation.<br>
Table X presents the results of the E\_HGSO algorithm<br>
and eight comparison algorithms for 8 datasets, including<br>
the mean and standard deviation of the fitness values and the<br>
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Table X presents the results of the E\_HGSO algorithm<br>
and eight comparison algorithms for 8 datasets, including<br>
the mean and standard deviation of the fitness values and the<br>
op Trable X presents the average adaptation.<br>
Table X presents the results of the E\_HGSO algorithm<br>
d eight comparison algorithms for 8 datasets, including<br>
d eight comparison algorithms for 8 datasets, including<br>
timal valu Table A presents the results of the E-HGSO algorithm<br>and eight comparison algorithms for 8 datasets, including<br>the mean and standard deviation of the fitness values and the<br>optimal value. The best results are highlighted and eight comparison aigorithms for 8 datasets, including<br>the mean and standard deviation of the fitness values and the<br>optimal value. The best results are highlighted in bold. In<br>terms of fitness values, a smaller value i the mean and standard deviation of the itness values and the optimal value. The best results are highlighted in bold. In the middler of fitness values, a smaller value indicates better algorithm performance. Upon reviving

Where *n*<sub>sel</sub> is the number of selected descriptors,  $N_{tot}$  is the<br>
total number of descriptors, and  $AC_{cs}$  is the precision of<br>
the other algorithms. These fir<br>
or fired free free contents of feature selection number: T opumal value. The best results are ingningined in bold. In<br>terms of fitness values, a smaller value indicates better<br>algorithm performance. Upon reviewing the results, it is<br>evident that the E\_HGSO algorithm consistently a terms or nuness values, a smaller value indicates better<br>algorithm performance. Upon reviewing the results, it is<br>evident that the E\_HGSO algorithm consistently achieved<br>the best results in all eight datasets. Additionally algorithm performance. Upon reviewing the results, it is<br>evident that the E\_HGSO algorithm consistently achieved<br>the best results in all eight datasets. Additionally, the overall<br>ranking of the E\_HGSO algorithm is signific evident that the E\_HGSO algorithm consistently achieved<br>the best results in all eight datasets. Additionally, the overall<br>ranking of the E\_HGSO algorithm is significantly ahead of<br>the other algorithms. These findings under the best results in all eight datasets. Additionally, the overall ranking of the E\_HGSO algorithm is significantly ahead of the other algorithms. These findings underscore the superior performance and effectiveness of the ranking of the E\_HGSO algorithm is significantly anead of<br>the other algorithms. These findings underscore the superior<br>performance and effectiveness of the E\_HGSO algorithm in<br>comparison to the alternative algorithms.<br>Fig Formance and effectiveness of the E\_HGSO algorithm in<br>mapsion to the alternative algorithms.<br>In sumpsion to the alternative algorithm in<br>Fig.5 displays box plots representing the classification<br>curacies obtained by running performance and effectiveness of the  $E$ <sub>1</sub>HGSO algorithm in<br>comparison to the alternative algorithms.<br>Fig.5 displays box plots representing the classification<br>accurates obtained by running the nine algorithms<br>independent comparison to the atternative argorithms.<br>
Fig.5 displays box plots representing the classification<br>
accuracies obtained by running the nine algorithms<br>
independently ten times on the eight datasets. These box<br>
plots provi rig.5 asplays box plots representing the classification<br>accuracies obtained by running the nine algorithms<br>independently ten times on the eight datastes. These box<br>plots provide a visual representation of the mean and<br>disp

mumber of selected descriptions,  $N_{\text{in}}$  is the combine of the E HGSO algorithm is significantly ahead of<br>descriptors, and  $AC_{\text{c},2}$  is the precision of the unkner algorithms. These findings unkner<br>or respectiven and accuracies obtained by running the nine algorithms<br>independently ten times on the eight datasets. These box<br>plots provide a visual representation of the mean and<br>dispersion of the data. From the figure, it is evident that maependently ten times on the eight datasets. These box<br>plots provide a visual representation of the mean and<br>dispersion of the data. From the figure, it is evident that the<br>E\_HGSO not only achieves high fitness on most da plots provide a visual representation of the mean and<br>dispersion of the data. From the figure, it is evident that the<br>E-HGSO not only achieves high fitness on most datasets but<br>also exhibits fewer outliers in the central d dispersion of the data. From the rigure, it is evident that the E\_HGSO not only achieves high fitness on most datasets but also exhibits fewer outliers in the central distribution of F\_HGSO. The consistent highlights the r E\_HGSO not only achieves nigh itmess on most datasets but<br>also exhibits fewer outliers in the central distribution of<br>results. This observation highlights the robustness of<br>E\_HGSO. The consistent high performance and reduc also exhibits rewer outliers in the central distributes<br>results. This observation highlights the robusti<br>E\_HGSO. The consistent high performance and<br>variability of the E\_HGSO further validate its effect.<br>In summary, our re sults. This observation inginights the robustness of HGSO. The consistent high performance and reduced riability of the E-HGSO further validate its effectiveness. In summary, our research results have conclusively monstrat E\_HGSO. The consistent nigh performance and reduced<br>variability of the E\_HGSO further validate its effectiveness.<br>In summary, our research results have conclusively<br>demonstrated that the algorithm we proposed exhibits<br>exce variability of the E\_HOSO further validate its effectiveness.<br>
In summary, our research results have conclusively<br>
demonstrated that the algorithm we proposed exhibits<br>
excellent performance in most cases. The algorithm n

Fig.6 illustrates the convergence curves of fitness for

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Best 1.2064E+00 1.2321E+00 1.2483E+00 1.2305E+00 1.2079E+00 1.2477E+00 1.28<br>
Rank 2 8 7 5 4 6<br>
Final Rank 16 55 61 35 28 49<br>
Final Rank 16 55 61 35 28 49<br>
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Curves, retaining four representative ones. The results algorith Rank 2 8 7 5 4 6 9<br>
Total Rank 16 55 61 35 28 49 72<br>
Final Rank 2 7 8 5 3 6 9<br>
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clearly indicate that, across the majority of dataset Total Rank 16 55 61 35 28<br>
Final Rank 2 7 8 5 3<br>
Curves, retaining four representative ones. The results algorithm, s<br>
clearly indicate that, across the majority of datasets, the three<br>
of its prede<br>
variants of the E\_HGSO in a strongglent problem. The substantial and the Hindustrian in the Hindustrian of the Hindustrian and the Hindustrian and the Hindustrian and the Hindustrian and the Hindustrian of the EHGSO algorithm in the series of th rves, retaining four representative ones. The results<br>algorithm, specifically designary indicate that, across the majority of datasets, the three<br>of its predecessor. These I<br>riants of the E\_HGSO algorithm demonstrate nota clearly indicate that, across the majority of datasets, the three<br>
variants of the E\_HGSO algorithm demonstrate notably<br>
variants of the E\_HGSO algorithm demonstrate notably<br>
notation diversity, vulneral<br>
distance the fea variants of the E\_HGSO algorithm demonstrate notably<br>
faster convergence speeds compared to the other algorithms,<br>
sonvergence speed. The<br>
ultimately reaching the lowest fitness values. Furthermore,<br>
focus on addressing th

1.2302E+00 1.2628E+00 1.3500E+00 1.2264E+00 1.2046E+00<br>
2.3308E-02 8.3031E-03 3.1029E-02 9.9729E-03 4.3574E-03<br>
1.2079E+00 1.2477E+00 1.2862E+00 1.2167E+00 1.2021E+00<br>
4 6 9 3 1<br>
28 49 72 31 13<br>
3 6 9 4 1<br>
algorithm, spec 2.3308E-02 8.3031E-03 3.1029E-02 9.9729E-03 4.3574E-03<br>
1.2079E+00 1.2477E+00 1.2862E+00 1.2167E+00 1.2021E+00<br>
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algorithm, specifically designed to overcome the limitations<br>
of its pr 1.2079E+00 1.2477E+00 1.2862E+00 1.2167E+00 1.2021E+00<br>
4 6 9 3 1<br>
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algorithm, specifically designed to overcome the limitations<br>
of its predecessor. These limitations include insufficient<br>
popul 1.20/9E-60 1.24//E-60 1.2602E-60 1.210/E-60 1.2021E-60<br>
4 6 9 3 1<br>
28 49 72 31 13<br>
29 10 11<br>
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1 11<br>
1 <sup>28</sup> <sup>49</sup> <sup>72</sup> <sup>31</sup> <sup>13</sup><br><sup>3</sup> 6 <sup>9</sup> <sup>4</sup> <sup>1</sup> <sup>13</sup><br>**algorithm, specifically designed to overcome the limitations<br>of its predecessor. These limitations include insufficient<br>population diversity, vulnerability to local optima,**  $\frac{3}{1}$  6 9 9 4 1<br>algorithm, specifically designed to overcome the limitations<br>of its predecessor. These limitations include insufficient<br>population diversity, vulnerability to local optima, and slow<br>convergence speed. search effectively, which can better adapt to the search advocines algorithm, specifically designed to overcome the limitations of the propulation diversity, vulnerability to local optima, and slow convergence speed. The i algorithm, specifically designed to overcome the limitations<br>of its predecessor. These limitations include insufficient<br>population diversity, vulnerability to local optima, and slow<br>convergence speed. The improvements made argorium, specincally designed to overcome the imitations<br>of its predecessor. These limitations include insufficient<br>population diversity, vulnerability to local optima, and slow<br>focus on addressing these shortcomings. The or its predecessor. Inese limitations include insurricient<br>population diversity, vulnerability to local optima, and slow<br>convergence speed. The improvements made in this study<br>focus on addressing these shortcomings. The ne population diversity, vulnerability to local optima, and slow<br>convergence speed. The improvements made in this study<br>focus on addressing these shortcomings. The new grouped<br>resulting in improved efficiency and the sality t



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algorithm is applied to feature selection concurrently. To antison state is performance in this context, eight datasets with demonstrate that F. HGSO excluding the selection concurrently. To demonstrate that E. HGSO exclu validate its performance in this context, eight datasets with<br>
The stress of the **Example 128**<br>
variable of the size are carefully selected from the size are carefully selected from the size are experimented in the size are expected from the size are carefully selected from the size are experimented i **Example 1988**<br>
Tig.6. Convergence curve of E-HGSO and other algorithms.<br>
Fig.6. Convergence curve of E-HGSO and other algorithms.<br>
In Fig.6. Convergence curve of E-HGSO and other algorithms.<br>
In through Friedman and Wilc 0.985<br>
Fig.6. Convergence curve of E\_HGSO and other algorithms.<br>
Fig.6. Convergence curve of E\_HGSO and other algorithms.<br>
through Friedman and Wilcoxon signed rank tests, which  $\begin{bmatrix} 6 \end{bmatrix}$  J. Zhong, L. Feng and<br>
con Fig.6. Convergence curve of E\_HGSO and other algorithms.<br>
Fig.6. Convergence curve of E\_HGSO and other algorithms.<br>
through Friedman and Wilcoxon signed rank tests, which  $\begin{array}{ll}\n & 6 & 7 & 8 & 9 & 10 & 0 & 1 & 2 & 3 \\
 & \times 10^4 & & & &$ FER FIG.6. Convergence curve of E\_HGSO and other algorithms.<br>
through Friedman and Wilcoxon signed rank tests, w<br>
confirm the significant differences between the algorit<br>
and reinforce the finding that E\_HGSO consiste<br>
ach Convergence curve of E\_HGSO and other algorithms.<br>
Tough Friedman and Wilcoxon signed rank tests, which<br>
inform the significant differences between the algorithms<br>
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confirm the significant differences between the algorithms<br>
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confirm the significant differences between the algorithms<br>
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UCI machine learning library. The experimental results<br>
demonstrate that E\_HGSO exhibits superior efficiency, problems. more comprehensive analysis and investigation of the<br>
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