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A Critical Examination of Optimization Algorithmic Developments, Applications, and Limitations in Crow Swarm Optimization Search Theory

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ABSTRACT

The Crow Swarm Optimization algorithm (CrSO) is a highly effective metaheuristic optimization technique inspired by the collective behavior of crow flocks and their strategies for hiding food. Drawing from the natural strategies crows use to protect and retrieve their food, CrSO has proven highly effective in solving complex optimization problems. Its ability to balance exploration and exploitation has made it a popular choice in various fields, including science, engineering, and data analysis. This paper comprehensively explores CrSO, beginning with its biological inspirations and extending to its mathematical foundations and algorithm framework. Additionally, it evaluates the CrSO's performance in real-world applications while critically examining its limitations to provide a balanced perspective on its strengths and areas for improvement. However, CrSO has limitations by critically examining some challenges, such as sensitivity to parameter settings, computational complexity in high-dimensional spaces, and potential convergence issues in multi-modal problems.

Keywords Crow Swarm Optimization Algorithm, Optimization problems, Swarm intelligence, Metaheuristic, Nature-inspired algorithm

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1. INTRODUCTION

In recent years, optimization algorithms have been widely applied to solve various complex problems across multiple domains. For instance, in engineering, these algorithms address challenges involving numerous constraints, a large number of decision variables, and intricate objective functions. Optimization algorithms can be broadly classified into two main categories: stochastic and deterministic. Stochastic algorithms are further divided into heuristic and meta-heuristic. While heuristic algorithms rely heavily on experimentation, meta-heuristic algorithms operate at more advance level, offering more sophisticated solutions.

Meta-heuristic algorithms can be categorized into four nature-inspired types (as shown in Figure 1). physics-based methods, swarm-based methods, evolution-based methods and human-based strategies [1, 2, 3].

Optimization problems themselves are classified into four categories: constrained or unconstrained, continuous or discrete, single or multi-objective and static or dynamic. Due to the inherent complexity of these problems, nature-inspired optimization algorithms have gained significant attention. These algorithms have demonstrated superior performance in solving high-dimensional problems, proving to be more powerful and robust in their search capabilities compared to traditional methods.

The Crow swarm optimization algorithm (CrSO) is a nature-inspired optimization algorithms introduced by Askarzadeh (2016) [3]. It mimics the intelligence behaviors of crow flock, particularly their process of hiding and retrieving food. Studies have demonstrated that CrSO outperforms other optimization algorithms, such as Genetic Algorithm (GA), Harmony Search (HS), and Particle Swarm Optimization (PSO), in term of both accuracy and convergence speed [**5, 6**]. Additionally, CrSO has proven to be highly effective in solving complex optimization problems [7].

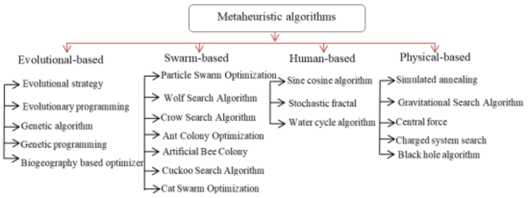

Figure 1. Meta-heuristic categories

2. CROW SEARCH AND ANALYSIS

2.1 Crow Swarm Optimization Algorithm

As shown in the Figure 2, optimization algorithms can be classified into three main categories: deterministic algorithms, stochastic algorithms, and hybrid algorithms, which combine elements of both [**9**]. Deterministic algorithms rely on fixed functions, specific data, and repeatable design variables. Unlike stochastic algorithms always produce the same outputs for the same inputs [**10**].

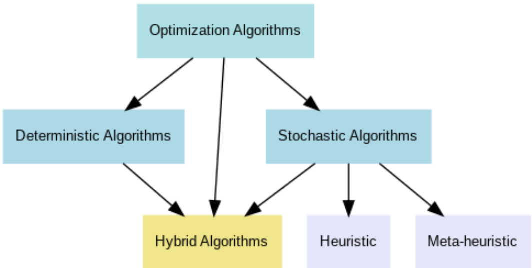

Figure2. The general classification of the optimization algorithms

The second category is stochastic algorithms. These algorithms incorporate random numbers in their processes. For example, the genetic algorithm is stochastic due to the random numbers used in the mutation operator. Each time the algorithm is executed, the paths may change, even if the final solutions do not differ significantly. Stochastic algorithms are further categorized into heuristic and meta-heuristic types.

In 2016, Askarzadeh introduced a meta-heuristic optimization algorithm called Crow Swarm optimization (CrSO) [4]. CrSO is inspired by the behavior of crow, particulary, their ability to hide and steal foods. Crows are considered among the most intelligent birds. They exhibit unique behaviors such as living in the flock, possessing excellent memory, stealing food from other crows, recognizing faces, warning their flock of potential threats, using sophisticated communication methods, and demonstrating self-awareness [18, 19].

As a methodology, CrSO operates in a D-dimensional environment. The size of the crow flock is represented by *n*, and the position of crow *i* at iteration *t* is denoted by X_d^t as described in Equation (1):

$$\mathbf{X^{i,t} = (X_1^{i,t}, X_2^{i,t}, \ldots\ldots\ldots\ldots, X_d^{i,t^{max}})} \quad (1)$$

Where *i=1,2,3,……,n, t=1,2,3,……,tmax* and *tmax* is the maximum number of iterations. Each crow has a memory *mi,t* that stores the best-visited location of its food source until the stopping iteration is reached [18]. The positions *X* are updated at each iteration as shown in Equation (2), until the stopping criterion is met [18].

$$\mathbf{m^{i,t} = m_1^{i,t}, m_2^{i,t}, \ldots\ldots\ldots\ldots, m_n^{i,t}} \quad (2)$$

There are two cases for updating the positions of crows [19, 20]. In the first case, crow *j* is unaware that crow *i* is following it. As a result, crow *j* does not update its position, allowing crow *i* to discover the hiding location of crow *j* (see Figure 3). When $ra_i \geq AP$, crow *i* updates its position according to Equation (3):

$$\mathbf{X^{i,t+1}} = \begin{cases} \mathbf{X^{i,t} + ra_i \times fl^{i,t} \times (m^{i,t} - X^{i,t})} & \mathbf{ra_i \geq AP} \\ \textbf{a random position} & \mathbf{ra_i < AP} \end{cases}$$

(3)

Here:

ra_i: A random number with a uniform distribution between 0 and 1.

AP: The awareness probability of crow j at iteration t.

$fl^{i,t}$The flight length of crow i at iteration t. the flight length $fl^{i,t}$ influence the search capability of CrSO [4] and play a crucial role in the convergence of the algorithm [21].

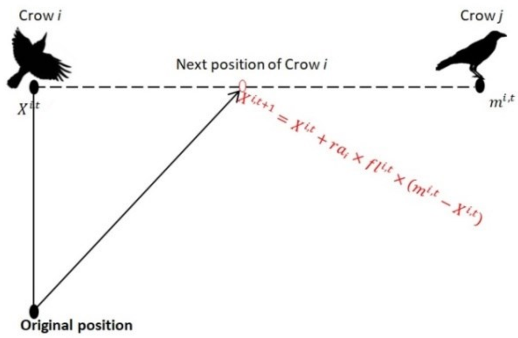

Figure3. Updating crow i position if $fl < 1$

As shown in Figure 4, the second case occurs when crow j realize that crow i is following it. In this case, crow j moves to a random position to protect its hidden food. Consequently, when ra_i<AP, the position of crow i is updated at iteration t+1 as described in Equation (3).

2.2 Implementing CrSO for solving Optimization Problems

CrSO utilizes a population of crows to find an optimal solution for optimization issues in a D-dimensional search space. The key advantages of CrSO optimization include simple code, fast convergence, and high efficiency. As illustrated in figure (4), the implementation of CrSO involves the following steps [4]:

1. Define the Optimization Problem and Adjustable Parameters:

CrSO involves four main parameters:

- *n*: The size of the crow flock.
- *tmax*: The maximum number of iterations, which serves as the termination criterion.
- *fl*: The flight length, which determines the balance between global and local searches.
- *AP*: The awareness probability, which controls the balance between diversification and intensification (see Figure 5).

2. Initialize the Position and Memory of Crow Randomly:

Since the crows have no prior experience, two vectors must be initialized randomly:

- The position of crow i at iteration t, denoted as $X^{i,t}$ (see Equation 1).
- The memory of crow i at iteration t, denoted as $m^{i,t}$ (see Equation 2).

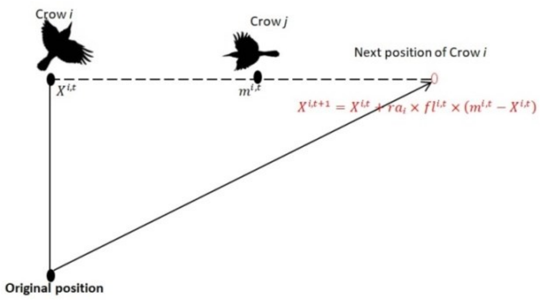

Figure 4. Updating crow *i* position if *fl>1*

3. **Calculate the Objective Function for Each Crow:**

By inserting the decision variable values into the objective function, the quality of the crows' positions is determined.

4. **Generate a New Position Based on Crow behavior:**

Each crow updates its position based on its inherent behavior. For example, crow i may follow another crow (e.g., crow j) to discover the hidden location of its food. The position of crow i is then updated using Equation (3). This process is repeated for every crow in the flock.

5. Check the Feasibility of the New Position:

Each crow evaluates whether its new position is feasible. If the new position is acceptable, the crow updates its location; otherwise, it remains in its current position.

6. Evaluate the Fitness Function for New Positions:

The fitness values are computed for each crow based on its updated position.

7. Update the Crows' Memory:

Each crow updates its memory if the new position yield a better objective function value than its current memory. The update rule is as follows:

$$m^{i,t+1} = \begin{cases} X^{i,t+1} & f(X^{i,t+1}) \text{ is batter than } f(m^{i,t}) \\ f(m^{i,t}) & \text{otherwise} \end{cases} \quad (4)$$

Here, $f(\,)$represents the objective function value for the selected position.

Check the Termination Criterion:

Step 4 through 7 is repeated iteratively until the maximum number of iterations (*tmax*) is reached. Once the termination criterion is met, the best position with the optimal objective function value is selected as the final solution to the optimization problem

2.1 The Essence and Efficiency of an Algorithm

The essence of an algorithm lies in its ability to perform a search correctly, ensuring that the required search is executed, though not necessarily efficiently [9]. An optimization algorithm generates a new solution for a given problem at each iteration or time step. This process can be represented by Equation (5):

$$\mathbf{X^{t+1} = A(X^t, p(t))} \quad (5)$$

Here, X^{t+1}represents the new optimization solution at iteration t, and A is a nonlinear algorithm that from transforms the current solution X^tinto X^{t+1}. The algorithm A depends on k parameters, denoted as *p(t)= (p1,p2,......,pk)*, which may vary with time or iteration [22].

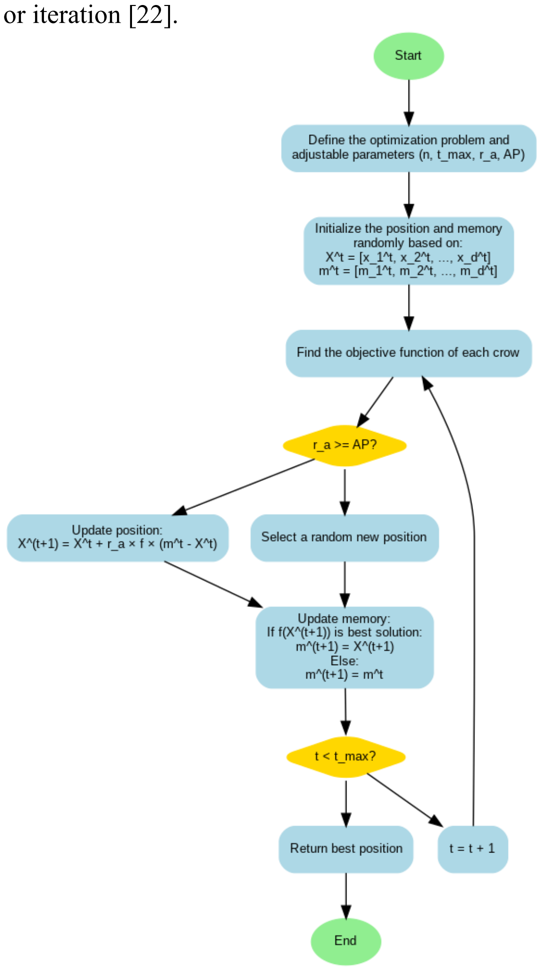

Figure 5. Flowchart CSA Optimization Algorithm

To find a new optimal solution for a problem with an infinite number of cases, the algorithm tests a subset of desired cases from all possible cases based on a predefined criterion. This is expressed in Equation (6):

$$\mathbf{S}(\boldsymbol{\psi}) \xrightarrow{\mathbf{A(t)}} \mathbf{S}(\boldsymbol{\theta}(\mathbf{X}^{\mathbf{t+1}})) \qquad (6)$$

Here, S represents the number of cases, ψ denotes all possible cases, and θ refers to the desired cases [27].

An algorithm can serve as a tool to tune a complex system. As indicated by Equation (6), the performance of an optimization algorithm may depend on the type of optimization problem being addressed. Moreover, whether an optimal solution is achieved (within a given number of iterations) depends on the chosen algorithm.

The efficiency of optimization algorithms is crucial to ensure the discovery of an optimal solution [23]. In mathematical programming, efficiency is typically measured using three criteria: implementation time, the number of fundamental evaluations, and memory usage [23].

Implementing time is one of the important measures for evaluating the efficiency of an optimization methodology. It can be measured in two ways:

- CPU Time: the actual time the processor takes to execute the code.
- Waiting Time: the time the programmer waits for the code to execute on the computer.

CPU time is generally more stable than the waiting time because it is independent of other computer operations and consistent for the same version of an operating system running on the same computer.

The second important measure is the number of fundamental evaluations. It refers number of times an optimization algorithm calls a subroutine to obtain fundamental information about the problem. Fewer evaluations typically indicate higher efficiency.

Additionally, memory usage is a less commonly used measure of efficiency. It refers to the mount of memory consumed by algorithm during execution.

Furthermore, the efficiency of an algorithm can also be evaluated by incorporation randomness. In this case, the algorithm may produce different results each time it is run, even when starting from the same initial point. Randomness-based optimization algorithms are highly diverse and include genetic algorithms, differential evolution, simulated annealing, ant colony optimization, bat algorithm, crow swarm optimization, bee algorithms, particle swarm optimization, firefly algorithm, harmony search, cuckoo search, and others [4, 8, 24, 25, 26, 27, 28].

2.4 Why is Crow Swarm Optimization So Efficient?

The CrSO is highly efficient due to its two key search capabilities: the tradeoff between randomization and local search, which enable it to solve real-world optimization problem effectively [29]. CrSO employs a random search technic to identify the best solution for a given problem. This approach ensures that the search space is explored more efficiently through the balance of randomization, increasing the probability of finding optimal solutions. This feature allows CrSO to discover new and improved solutions for complex problems [30].

CrSO is considered an enhanced version of Particle Swarm Optimization (PSO) [31, 32]. While PSO requires tuning four adjustable parameters—individual learning factor, maximum velocity, inertia weight, and social learning factor—and Genetic algorithms (GA) require 6 parameters (crossover probability, crossover method, selection method, mutation probability, mutation method, and replacement method) [32], CrSO just requires adjusting two parameters: flight length (fl) and awareness possibility (AP) [33]. The success of any optimization algorithm heavily depends on the appropriate tuning of its parameters [34], and CrSO's in this regard makes it more efficient compared to other optimization algorithms.

The flight length (fl) parameter significantly impacts CrSO's performance. Smaller values of *fl* help in finding local optimum solution, while the large *fl* helps to gain the global optimum solution. On the other hand, the awareness possibility (*AP*) plays a crucial role in balancing the intensification and diversification phases of the CrSO. Lower values of *AP* encourage the exploitation of known regions in the search space, whereas higher values promote the exploitation of undiscovered regions in a randomized manner [34].

These advantages make CrSO easy to implement, and highly efficient, and capable of converging to optimal solution quickly [35]. Numerous studies and applications have demonstrated the efficiency of CrSO, as will be discussed in detail in the following section.

3 APPLICATIONS

CrSO has been widely applied in various fields of optimization and computational intelligence, demonstrating high efficiency in numerous applications. As shown in table 1, it has been particularly effective in engineering design. For instance, a modified version of CrSO was used to optimize the operation of the hybrid energy system that composes of photovoltaic (PV) panels, pumped hydro storage (PHS), and diesel generator. This approach achieved higher accuracy compared to other methodologies [35].

Additionally, CrSO has been employed to solve the optimal reactive power dispatch

Table 1: Engineering Applications

Engineering design apps.	Methods	Min	Mean	Max	Std
the operation of the hybrid energy system that composes of photovoltaic (PV), pumped hydro storage (PHS) and diesel generator [35]	GA	72.2433	82.4223	87.6319	4.7368
	PSO	74.3452	89.3816	94.7352	4.1307
	CSAAC-AP (α=2)	**67.0566**	**78.8633**	**84.7844**	**3.4788**
three-bar truss design, pressure vessel design, tension/compression spring design, welded beam design, gear train design and gear train design [4]	GA3	6308.4970	6293.8432	6288.7445	7.4133
	GA4	6469.3220	6177.2533	6059.9463	130.9297
	CPSO	6363.8041	6147.1332	6061.0777	86.45
	HPSO	6288.6770	6099.9323	6059.7143	86.20
	G-QPSO	7544.4925	6440.3786	6059.7208	448.4711
	QPSO	8017.2816	6440.3786	6059.7209	479.2671
	PSO	14076.3240	8756.6803	6693.7212	1492.5670
	CDE	6371.0455	6085.2303	6059.7340	43.0130
	UPSO	9387.77	8016.37	6154.70	745.869
	PSO-DE	N.A	6059.714	6059.714	N.A
	ABC	N.A	6245.308144	6059.714736	205
	(l + k)-ES	N.A	6379.938037	6059.701610	210
	TLBO	N.A	6059.71434	6059.714335	N.A.
	CSA	**7332.84162110**	**6342.49910551**	**6059.71436343**	**384.94541634**
the optimal power flow (OPF) problem related to the RDGs [19]	DE	1.9687×10^{-15}	1.5408×10^{-4}	0.0043	7.3369×10^{-4}
	ABC	2.5701×10^{-15}	0.0030	0.0126	0.0024
	GSA	3.4768×10^{-22}	5.4439×10^{-21}	1.6715×10^{-20}	4.1473×10^{-21}
	ICSA	$\mathbf{1.4024 \times 10^{-32}}$	$\mathbf{1.9404 \times 10^{-30}}$	$\mathbf{6.3192 \times 10^{-29}}$	$\mathbf{1.0674 \times 10^{-29}}$
the multi-parameter evaluation problem of groundwater quality [37]	PPSOGSA	618.77	619.21	619.98	0.5488
	TLBO	618.66	619.06	619.36	0.4576
	PSO	633.32	634.02	635.44	0.9498
	CSA-PSO	**617.09**	**617.32**	**617.98**	**0.3812**
electromagnetic benchmark problem [38]	NIM	-	-	1.2864	-
	BP	-	-	1.0280	-
	ELM Model	-	-	1.0648	-
	CSA-ELM	**-**	**-**	**1.0654**	**-**
electromagnetic benchmark problem [39]	CSA	3.1308	5.4788	8.5990	1.5972
	MCSA	**2.0619**	**3.8435**	**4.7021**	**0.3592**
enhancing electrical distribution networks [40]	ACO	646.383	-	-	-
	Proposed CSA	**705.673**	**-**	**-**	**-**
energy problems, the combined economic and emission dispatch (CEED) problem [41]	NR	3.2706	-	-	-
	GA	3.2846	-	-	-
	HGA	3.1045	-	-	-
	CSA	**2.96**	**-**	**-**	**-**
the optimal reactive power dispatch problem [36]	**CSA -IEEE 30**	**2.8507**	**-**	**-**	**-**
	CSA -IEEE57	**15.1934**	**-**	**-**	**-**
	CSA -IEEE118	**76.7783**	**-**	**-**	**-**
	CLPSO -IEEE30	4.5615	-	-	-
	CLPSO -IEEE57	24.5152	-	-	-
	CLPSO -IEEE118	131.99	-	-	-
	GSA -IEEE30	4.5143	-	-	-
	GSA -IEEE57	23.4611	-	-	-
	GSA –IEEE118	127.7603	-	-	-
	SOA-IEEE57	24.2654	-	-	-
	SOA-IEEE118	114.9501	-	-	-

problem [36]. It has also been successfully applied to the optimal design of third-order resonance-free passive filters in distribution networks solved with efficient results [20].

CrSO has demonstrated promising results in solving six engineering optimization problems: three-bar truss design, pressure vessel design, tension/compression spring design, welded beam design, and gear train design [4]. Moreover, in engineering applications, Crow Swarm Optimization has shown superior performance compared to other optimization algorithms for a wide range of problems. These include the optimal power flow (OPF) problem related to renewable distributed generation (RDGs), the multi-parameter evaluation problem of groundwater quality, electromagnetic benchmark problem, enhancing electrical distribution networks, energy-related problems, and the combined economic and emission dispatch (CEED) problem [17, 37, 38, 39, 40, 41].

Table 2. Medical Applications

Healthcare apps.	**Methods**	**Accuracy**	**Average**
DNA fragment assembly problem [30] (based on Statistical Ranking Color Scheme (SRCS))	**CSA-P2M ∗Fit**	-	**1.6 /0.4**
	P2M ∗Fit	-	−2/ −1.6
	GA-P2M ∗Fit	-	0.4/ 1.2
diagnosing medical problems [42] (for the data sets DS4)	**CFCSA**	**0.986**	-
	BCSA	0.907	-
	BALO	0.791	-
	CALO	0.930	-
	bat	0.748	-
predict Parkinson's disease [43]	**OCSA**	**0.882**	-
	CCSA	0.842	-
the diagnosis in different brain diseases [44] for the data set Z144 based on the feature similarity index (FSIM)	**CSA**	**0.9060**	-
	DE	0.8966	-
	HS	0.9015	-

In addition, CrSO has been applied in the healthcare application, as summarized in Table 2. The study [31] combined CrSO with the Overlay Layout Consensus (OLC) approach to accelerate the search process and enhanced the quality of the results for the DNA fragment assembly problem. Anter et al. [42] developed a hybrid crow swarm optimization (CFCSA) for diagnosing medical problems. Furthermore, [43] proposed an optimized version of the crow swarm optimization (OCSA) to predict Parkinson's disease, achieving the highest accuracy compared to other algorithms used for this optimization problem. CrSO has also been demonstrated higher efficiency in assisting the diagnosis of various brain diseases, outperforming other used methodologies [44].

On the other hand, CSA has been used to minimize the total weighted tardiness in single-machine total weighted tardiness (SMTWT) scheduling problems that depend on setup times [45]. Lakshmi et al. [46] combined the CSA with K-means algorithm to cluster data efficiently and achieve a global optimal solution. Furthermore, a hybrid GWO with CSA (GWOCSA) was proposed to solve feature selection problems [47]. This methodology demonstrates a high capability for solving real-world complex problems compared to other algorithms.

Gupta et al. [48] utilized a modified crow swarm optimization (MCSA) to extract usability features from the hierarchical model, achieving optimal solution. Additionally, [49] introduced a novel metaheuristic optimizer called the Chaotic Crow Swarm Optimization (CCSA). It was applied with superior efficiency to optimize feature selection by maximizing classification performance and minimizing the number of selected features. Recent studies have further demonstrated that CSA can outperform other optimization algorithms in various applications [50, 51, 52, 53, 54, 55].

4 DISCUSSION AND CONCLUDING REMARKS

The Crow Swarm Optimization (CrSO) is a swarm intelligence-based algorithm that is highly effective in solving optimization problems. As a result, CrSO applies in various fields, including sciences, engineering, features clustering. While CrSO demonstrates strong global convergence capabilities, it still faces several challenges that require further research. These include its tendency to update positions randomly, occasional inefficiency in selecting global optimization solutions and slower convergence rates when dealing with multi-modal optimization problems [57, 58]. Addressing these limitations will be crucial for enhancing the algorithm's performance in future studies.

Most optimization algorithms are highly effective in practice applications but often lack robust theoretical analysis. This creates a significant gap between theory and practice, which remains a key challenge. While researchers can successfully apply these algorithms in practice, they often struggle to understand why a particular algorithm works or how to improve it without a deeper understanding of its underlying mechanisms.

Another critical issue affecting the efficiency of meta-heuristic algorithms is their dependence on specific parameters. For instance, the performance of the crow swarm optimization is heavily influenced by these parameters [27]. As a result, selecting the appropriate parameter setting becomes an optimization problem in itself. This has made parameter tuning an important area of research [56]. Giving these challenging, the crow swarm optimization may inspire further research and applications in the near future, potentially offering advantages over other optimization algorithms.

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