Review of Research on Chemical Reaction Optimization Algorithm

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Abstract:

As an intelligent optimization algorithm, the chemical reaction optimization algorithm has many advantages of strong robustness, flexible design, and easy implementation. Therefore, it is widely used to solve optimization problems in kinds of different fields. Aiming at the vacancy of the chemical reaction optimization algorithm in the research review, based on the introduction of the basic principles of chemical reaction optimization algorithm, this article briefly describes the theoretical research and parameter settings of chemical reaction optimization algorithm. And from the perspective of improvement and application, several improved methods and applications of chemical reaction optimization algorithm in some fields. Then the improved advantages, disadvantages and applicable scenarios of the algorithm in terms of design framework, molecular structure and operation operators are analyzed and summarized. At the same time, the advantages, disadvantages and applicable scenarios of the hybrid algorithms which combine the chemical reaction optimization algorithm with other algorithms are also analyzed and summarized. Finally, the current situation and future development of chemical reaction optimization algorithm are summarized and prospected, which would provide inspiration and reference for other follow-up researches.

Keywords: Chemical reaction optimization algorithm, Swarm intelligence, Review, Algorithm improvement, Hybrid algorithm.

I. INTRODUCTION

Chemical Reaction Optimization Algorithm (CROA) [1] is an intelligent optimization algorithm proposed by LAM et al. in 2010. Inspired by the nature of chemical reactions, it seeks the optimal solution by imitating the changes in the movement of molecules during chemical reactions.

The chemical reaction optimization algorithm has the advantages of strong robustness, flexibility of algorithm design and simplicity of software implementation. Since it was proposed, it has attracted much attention from academia and has been widely used in various fields, such as: combinatorial optimization, control and identification, resource management, communication network and so on. In addition, articles on the application, improvement and algorithm fusion of chemical reaction optimization algorithm are also

emerging in an endless stream. However, there are few domestic and foreign articles on the research review of chemical reaction optimization algorithm. Therefore, this paper first briefly introduces the principle of the chemical reaction optimization algorithm and the basic molecular operations of the four elementary reactions, and summarizes the theoretical basis and parameter setting research of the chemical reaction optimization algorithm. Then, a comprehensive research review of chemical reaction optimization algorithm. Then, a comprehensive research review of chemical reaction optimization algorithm is carried out from the perspective of improvement and application. It provides convenience for other scholars to understand the progress and achievements of CROA, and also provides inspiration for the continued research and improvement of CROA. It is expected that this algorithm can be used to solve more practical problems.

II. CHEMICAL REACTION OPTIMIZATION ALGORITHM

2.1 Principle of Chemical Reaction Optimization Algorithm

Chemical reaction optimization algorithm is inspired by the nature of chemical reactions. The chemical reaction is a natural process by which a substance changes from an unstable state to a stable state. From a microscopic point of view, a chemical reaction starts with some unstable molecules with excess energy, and the molecules interact through a series of elementary reactions and transform into stable molecules with the lowest energy. The chemical reaction optimization algorithm simulates this molecular motion and change process in the chemical reaction. The process of optimizing the objective function is regarded as a chemical reaction process in an airtight container, and four primary reactions are adopted: collision, decomposition, exchange and synthesis. Different molecular structure (ω) represents different solution to the problem. Molecules are the main body of the algorithm to perform operations. Each molecule contains two kinds of energy, kinetic energy (*KE*) and potential energy (*PE*), following the law of energy conservation. The kinetic energy reflects the ability of the molecule to undergo basic reactions, and the potential energy represents the objective function obtained by the chemical reaction optimization algorithm is the molecule with the lowest potential energy in the primary reaction.

2.2 Basic Molecular Operations

(1) collision reaction

Only one molecule is involved in the collision reaction, and the slight collision with the container wall produces a new molecule with little change in structure and energy. Assuming that the original molecular structure is ω and the new molecular structure generated is ω , the conditional formula for the collision reaction to occur is:

$$PE_{\omega} + KE_{\omega} \ge PE_{\omega} \tag{1}$$

where PE_{ω} is the potential energy of the newly generated molecule. In the collision reaction, the original molecule will lose a certain kinetic energy value for each collision, and the lost kinetic energy

value will be stored in the energy buffer area of the container. Let a system parameter *KElossRate* be the maximum percentage of kinetic energy loss, so $q \in [0, KElossRate]$, the ratio of kinetic energy loss is q. According to the law of conservation of energy, the new molecular kinetic energy can be obtained as:

$$KE_{\omega} = \left(PE_{\omega} + KE_{\omega} - PE_{\omega}\right) \times (1 - q)$$
⁽²⁾

After the collision reaction is over, update the cached energy *buffer* in the energy buffer area to:

$$buffer = buffer + (PE_{\omega} + KE_{\omega} - PE_{\omega}) \times q$$
(3)

(2) decomposition reaction

Only one molecule is involved in the decomposition reaction, but it collides violently with the walls of the container, producing two new molecules. The molecular structure of the new molecule is quite different from that of the original molecule, and the energy changes are also large. Assuming that the original molecular structure is c, and the new molecular structures generated are ω_1 and ω_2 , respectively, the conditional formula for the decomposition reaction to occur is:

$$PE_{\omega} + KE_{\omega} \ge PE_{\omega} + PE_{\omega}$$
(4)

where PE_{ω_1} and PE_{ω_2} are the potential energies of the two newly generated molecules, respectively. Let k be a random number in the range of 0 to 1. According to the law of conservation of energy, the kinetic energy of the two new molecules can be obtained as:

$$KE_{\omega_{1}} = \left(PE_{\omega} + KE_{\omega} - PE_{\omega_{1}} - PE_{\omega_{2}}\right) \times k$$
(5)

$$KE_{\omega_{2}} = \left(PE_{\omega} + KE_{\omega} - PE_{\omega_{1}} - PE_{\omega_{2}}\right) \times (1-k)$$
(6)

According to formula (4), it can be concluded that the equation is established only when KE_{ω} is large. However, the reality is that this equation is difficult to satisfy all the time. Therefore, in order to ensure that the decomposition reaction can occur normally, it is necessary to supplement it with the cached energy stored in the energy buffer in the previous collision reaction to increase the probability of the decomposition reaction. So, when formula (4) is difficult to satisfy, the decomposition reaction can still be realized if the following conditional formula is satisfied:

$$PE_{\omega} + KE_{\omega} + buffer \ge PE_{\omega} + PE_{\omega}$$
(7)

In addition, in order to prevent the value of the cached energy *buffer* from accumulating too much and affecting the kinetic energy value of the new molecule, the kinetic energy value of the new molecule becomes very large, which in turn affects the subsequent primary reactions. Therefore, four independent

random numbers between 0 and 1 of a_1 , a_2 , a_3 and a_4 are introduced to limit the kinetic energy value of the new molecule. At this time, according to the law of conservation of energy, the kinetic energy expressions of the two new molecules become:

$$KE_{\omega_1} = \left(PE_{\omega} + KE_{\omega} + buffer - PE_{\omega_1} - PE_{\omega_2}\right) \times a_1 \times a_2$$
(8)

$$KE_{\omega_{2}} = \left(PE_{\omega} + KE_{\omega} + buffer - PE_{\omega_{1}} - PE_{\omega_{2}} - KE_{\omega_{1}}\right) \times a_{3} \times a_{4}$$
(9)

After the decomposition reaction is over, update the cache energy *buffer* in the energy buffer area to:

$$buffer = buffer + PE_{\omega} + KE_{\omega} - PE_{\omega_1} - PE_{\omega_2} - KE_{\omega_1} - KE_{\omega_2}$$
(10)

(3) exchange reaction

There are two molecules involved in the exchange reaction, and there is a slight collision between the molecules to generate two new molecules. The molecular structure of the new molecule is similar to that of the original molecule, and a small amount of energy is exchanged between the molecules. Assuming that the original molecular structures are ω_1 and ω_2 , respectively, and the new molecular structures generated are ω_1 and ω_2 , respectively, and the exchange reaction to occur is:

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \ge PE_{\omega_1} + PE_{\omega_2}$$
(11)

where PE_{ω_1} and PE_{ω_2} are the potential energies of the two newly generated molecules, respectively. Let *p* be a random number in the range of 0 to 1. According to the law of conservation of energy, the kinetic energy of the two new molecules can be obtained as:

$$KE_{\omega_1} = \left(PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} - PE_{\omega_1} - PE_{\omega_2}\right) \times p \tag{12}$$

$$KE_{\omega_{2}} = \left(PE_{\omega_{1}} + PE_{\omega_{2}} + KE_{\omega_{1}} + KE_{\omega_{2}} - PE_{\omega_{1}} - PE_{\omega_{2}}\right) \times (1-p)$$
(13)

After the exchange reaction is over, because the overall energy loss is negligible, the value of the cached energy wxx1 in the energy buffer area remains unchanged.

(4) synthesis reaction

There are two molecules involved in the synthesis reaction, but the collision between the molecules is violent, and a new molecule is generated. The resulting new molecular structure has a huge gap with the original molecular structure, and the energy changes greatly. Assuming that the original molecular structures are ω_1 and ω_2 respectively, and the resulting new molecular structure is ω' , the conditional formula for the synthesis reaction to occur is:

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \ge PE_{\omega_1}$$
(14)

where PE_{ω} is the potential energy of the newly generated molecule. According to the law of conservation of energy, the kinetic energy of the new molecule is expressed as:

$$KE_{\omega} = PE_{\omega} + PE_{\omega} + KE_{\omega} + KE_{\omega} - PE_{\omega}$$
(15)

2.3 Chemical Reaction Optimization Algorithm Features

(1) The chemical reaction optimization algorithm is a design framework that allows different operators to be deployed to solve different problems.

(2) The superiority of the chemical reaction optimization algorithm depends on the transformation and transfer of energy in different entities and different forms while following the law of energy conservation.

(3) The characteristics of other properties that can be incorporated into the molecular structure make the design of different operators more flexible, and also make the CROA algorithm more flexible.

(4) According to the characteristics of the four primary reactions in the chemical reaction optimization algorithm, the collision force of the collision and the exchange reaction is slight, and the new molecular structure and energy generated do not change much, which are suitable for searching for local optimal solutions; the collision force of the decomposition and the synthesis reaction is intense, and the new molecular structure and energy generated vary greatly, which are suitable for jumping out of the local search for the global optimal solution. Therefore, the chemical reaction optimization algorithm has the characteristics of fast convergence speed and strong robustness, and can effectively avoid falling into local optimum.

(5) Compared with other intelligent optimization algorithms, the chemical reaction optimization algorithm has less setting parameters, simple algorithm and easy implementation. At the same time, the parallelization of the chemical reaction optimization algorithm is also easy to implement and modify because of the variability of the population and the fact that no synchronization between computational units is required.

(6) During the operation of the chemical reaction optimization algorithm, the feedback information is not used enough, which makes it easy to fall into redundant iterations in the solution process, especially in the later stage of the solution, resulting in a greatly reduced solution rate.

III. THEORETICAL RESEARCH ON CHEMICAL REACTION OPTIMIZATION ALGORITHM

In terms of theoretical research on chemical optimization algorithms, Jin et al. [2] realized two solution representations based on permutation and vector, and proved that the vector-based representation is better than the permutation-based representation in the grid scheduling problem of independent tasks. Lam et al. [3] proposed a real-coded version of the chemical reaction optimization algorithm in 2012: real-coded chemical reaction optimization (RCCRO), which makes the algorithm suitable for solving continuous optimization problems after simple adjustments. This not only broadens the scope of application of the

algorithm to a certain extent, but also provides a possibility for mathematical verification of the algorithm performance in the later stage. At the same time, in order to reduce the influence of the perturbation function on the chemical reaction optimization algorithm for solving continuous problems, Yu et al. [4] studied the performance of the chemical reaction optimization algorithm for solving different continuous problems under different perturbation functions. This also provides prior knowledge and inspiration for designing chemical reaction optimization algorithms for different optimization problems later. Stegherr et al. [5] implemented a parallelized variant of the chemical reaction optimization algorithm to reduce convergence time and scalability by exploiting a multi-core computing architecture.

Lam et al. [6] proved the global convergence of the algorithm from the perspective of mathematical formula derivation by modeling the chemical reaction optimization algorithm as a finite absorption Markov chain on the basis of the real number coded version of the chemical reaction optimization algorithm. And the necessary conditions for the algorithm to converge to the global optimal solution, the convergence speed and the expected time to reach the first optimal solution are analyzed theoretically. This provides the necessary theoretical basis for studying the utility of chemical reaction optimization algorithm.

IV. CHEMICAL REACTION OPTIMIZATION ALGORITHM PARAMETER SETTIINGS

The parameters of the chemical reaction optimization algorithm mainly include the initial number of molecules (PopSize), the determination factor of collision type (MoleColl), the maximum percentage of kinetic energy loss (KElossRate), the initial value of kinetic energy (InitialKE), the judgment factor of collision and decomposition reaction (α), and the judgment factor of exchange and synthesis reactions (β) . Where *MoleColl* is used to select the reaction type of monomolecular or bimolecular, and determines the number of molecules in which the primary reaction occurs; the judgment factors α and β are used to control the probability of decomposition and synthesis reactions, and determine the ability of the algorithm to jump out of the local optimum. Reference [7] gives suggested values for these parameters: PopSize=10; *MoleColl*=0.2; *KElossRate*=0.2; *InitialKE*=1000; $\alpha = 500$; $\beta = 10$. However, when solving practical problems, in order to maximize the optimization performance of the chemical reaction optimization algorithm on a specific problem, some parameter tuning needs to be performed to determine the best combination of parameter values. For example, literature [8] proposed to use a dynamic change strategy to control the values of key parameters α and β to improve the efficiency of problem solving and balance the relationship between local optimization and global optimization. Reference [9] analyzed the influence of different parameter values on the performance of the algorithm through the method of experimental design. It was concluded that the three parameters *InitialKE*, *KElossRate* and β jointly determine the convergence speed of the algorithm and the ability to jump out of the local optimum. All of these provide guidance for the parameter setting of chemical reaction optimization algorithm in solving other practical problems, and also provide reference for the study of parameter combination setting and self-adaptive parameter study in the later stage.

In order to reduce the workload of parameter adjustment in the chemical reaction optimization algorithm, the literature [10] simplified the parameters of the standard chemical reaction optimization algorithm into three categories: energy-related, reaction-related, and real-number coding-related. And an adaptive scheme is proposed to automatically adjust the corresponding parameter values, so that the algorithm can be better adapted to different practical problems.

V. RELATED APPPLICATION OF CHEMICAL REACTION OPTIMIZATION ALGORITHM

The flexibility and ease of implementation of the algorithmic framework design enable chemical reaction optimization algorithms to be widely applicable to different practical problems, while having the potential to solve problems that have not been successfully solved by other algorithms.

5.1 Application of CROA in Combinatorial Optimization Field

Reference [11] applied the chemical reaction optimization algorithm to solve the classical traveling salesman problem (TSP). The algorithm framework and four elementary reactions of the chemical reaction optimization algorithm were designed in a discrete problem environment, and the effectiveness of the algorithm was verified by the experimental simulation of the TSP data set.

Reference [12] applied chemical reaction optimization algorithm to optimize discrete network reconfiguration (NR) problems to improve the performance and reliability of modern power distribution systems.

5.2 Application of CROA in Control and Identification Field

Reference [13] applied the chemical reaction optimization algorithm to solve the population transfer problem that it proposed based on the Markov open queue network model. The population transition probability matrix was manipulated to maximize the probability of general streaming. The simulation results showed that the chemical reaction optimization algorithm had better performance than other control population transfer strategies.

According to the characteristics of chemical reaction optimization algorithm with strong global optimization ability, literature [14] combined the mixed sensitivity method in H_{∞} control theory, and proposed a H_{∞} -PID controller design method based on chemical reaction optimization algorithm. It could take into account the excellent performance of PID controller and H_{∞} controller.

Reference [15] applied the chemical reaction optimization algorithm to solve the problem of handwritten character recognition in Bengali. The recognition accuracy of the model was improved by designing the algorithm to search for sub-images with the most obvious features.

5.3 Application of CROA in Resource Management Field

Reference [16] applied the chemical reaction optimization algorithm to optimize the scheduling problem of robotic manufacturing cells. Molecules were selected for primary reaction by linear sorting selection based on the number of iterations, and then local search was performed after the primary reaction was completed, which improved the convergence speed of the algorithm and avoided the algorithm from falling into local optimum.

Reference [17] applied the chemical reaction optimization algorithm to solve the wind-based economic emission scheduling problem. The concept of quasi-opposition based learning was introduced, and the algorithm convergence speed was accelerated by initializing the quasi-backward seed cluster and generating the quasi-backward population by using the hopping rate.

Reference [18] proposed a micro-cloud selection strategy based on the chemical reaction optimization algorithm for the dual-objective micro-cloud selection optimization problem in the mobile cloud environment. It reduced the energy consumption of mobile devices while improving application performance in mobile cloud environments. However, there was still a certain gap between the experimental simulation environment of this study and the real environment, and it was necessary to consider adding enough variable factors to make the results close to the real situation.

Reference [19] proposed a fog computing in-vehicle network architecture based on non-orthogonal multiple access for the resource management problem in the internet of vehicles. The resource management problem was decomposed into two sub-problems: sub-channel and power allocation. Then the chemical reaction optimization algorithm and the chemical reaction optimization algorithm of the real number coding version were used to solve these two sub-problems respectively, which improved the energy efficiency of the system.

5.4 Application of CROA in Communication Network Field

According to the advantages of fast convergence speed and flexible design of chemical reaction optimization algorithm, literature [20] proposed an evolutionary algorithm based on chemical reaction optimization algorithm to solve the network coding optimization problem. The number of coding links in the network was minimized at a given target transmission rate.

Reference [21] designed multiple operators under the framework of chemical reaction optimization algorithm, so that chemical reaction optimization algorithm could generate feasible solutions that satisfied the constraints of cognitive radio spectrum allocation problem. The effectiveness and superiority of the algorithm were proved by simulation experiments.

VI. IMPROVEMENT AND APPLICATION OF CHEMICAL REACTION OPTIMIZATION ALGORITHM

The chemical reaction optimization algorithm is a design framework in which other properties can be incorporated into the molecular structure. Therefore, when solving practical problems, it is often possible to design, combine, and improve chemical reaction optimization algorithm according to the specific nature of the problem, so as to find the best algorithm that can solve specific problems. The following mainly introduces the improvement and application of chemical reaction optimization algorithm in some practical problems in recent years from the aspects of design framework, molecular structure, operation operators and other improvements, as shown in TABLE I.

TABLE I. Summary of advantages, disadvantages and applications of improved chemical reaction optimization algorithm

Impro	Na	Improvement mechanism	Advanta	Disadva	Appli
vement	me		ge	ntage	cation
type					Scenario
Design	CR	Divide the iteration phase	Ability	Compare	Task
Framework	O_V2	into two parts. In the first part,	to solve	d with the	scheduling
	[2]	only the collision reaction and	large-scale	particle	problems in
		the decomposition reaction are	problems.	swarm	grid
		allowed to occur. After reaching		optimization	computing.
		a predefined number of		algorithm, the	
		iterations, the second part		convergence	
		begins, which is similar to the		speed of the	
		entire iterative phase of the		improved	
		specification framework, but		algorithm is	
		excludes decomposition		still slower.	
		reaction.			
	VN	Combined with the	It can	Extend	Task
	S-CRO	constrained critical path	take into	planning time	scheduling
	[22]	rearrangement strategy, a	account the	when	and
		variable neighborhood search	global	resources are	subcontract
		method with balanced	scheduling	insufficient.	ing
		neighborhood structure is	perspective		optimizatio
		designed.	while		n of road
			ensuring the		constructio
			inted unning		n schedule
			of the		planning
			rlan		hatara gana
			pian.		neterogene
					resource
					environme
					nt
Molec	D	Bimolecular structure: one	Ontimiza	The	Direct
ular	MSCR	is used to encode the execution	tion speed and	space	ed acyclic
Structure	0 [23]	order of tasks in the DAG job	capabilities	complexity is	graph task
_ u u cui c	0 [=0]	and the other is used to encode	have been	high.	scheduling
		the mapping of tasks to	improved.	0	problem.

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		(1)			
		compute nodes.			
	O MOCR O [24] IC ROA [25]	Multi-objective optimization problems are handled using a Pareto sorting scheme, and an orthogonal experimental design with quantitative techniques is used to generate dispersed initial population molecules in the initial stage. The velocity and position update formulas of particle swarms are introduced into the disturbance function of the molecular structure update expression to improve.	The performance is better than the comparison algorithm MOPSO. Compare d with CROA, it converges quickly and does not get stuck in local optimum.	Compare d with NSGA-II, the improvement effect is not significant. Compare d with the particle swarm optimization algorithm, the improvement effect is not	The multi-objec tive optimal design problems for brushless DC motors. Econo mic evaluation problem of power smoothing in wind-hydro
	IC RO [26]	The velocity and position update formulas of particle swarms are introduced into the perturbation function of the molecular structure update expression for improvement, and the elite retention strategy is introduced in the iterative	It has better optimization effect and faster convergence speed than CRO.	Lack of comparative arguments with other types of algorithms.	wind-nyulo gen-fuel grid-conne cted systems. Desig n optimizatio n of high-speed brushless DC motor.
Operati on Operator	M OECRO /D [27]	process. Polynomial mutation and multi-molecular collision operators are introduced in exchange reaction and synthetic reaction.	A non-dominate d solution set with good convergence and diversity can be obtained.	The degree of convergence on discontinuous benchmark functions is not good enough.	20 benchmark functions.
	VN CRO [28]	The collision reaction is designed and realized by the experience learning domain structure and the variable-step domain search; the exchange reaction is designed and realized by the priority process cross-operation.	The advantages of solving large-scale examples are obvious.	The algorithm complexity is increased.	The reentrant scheduling problem with uncertain processing time.
	Hy brid Artificia l Chemic	in the Artificial Chemical Reaction Optimization Algorithm (ACROA) [30].	Ine global search ability and convergence ability are	nt will consume more CPU time in some cases.	0-1 knapsack problem.

	al		obviously		
	Reactio		better than the		
	n		comparison		
	Optimiz		algorithms.		
	ation				
	Algorith				
	Aigoniui				
	m [29]				
	IM	The new cyclic shift	It	Compare	The
	CRO	operator and the new two-step	performs	d with	shortest
	[31]	crossover operator are added to	better than	CRO_SCS,	common
		the decomposition reaction and	other	IMCRO does	super-sequ
		the exchange reaction,	heuristics on	not	ence
		respectively	random and	significantly	problem
		respectively.	real	reduce the	problem.
			icai		
			sequences.	average	
				length of the	
				shortest	
				common	
				super-sequenc	
				e.	
Other	NC	The new fast	The	It cannot	Multi-
Improveme	RO [32]	non-dominated sorting method	optimal	solve	objective
nts		with quasi-linear average time	solution	problems with	optimizatio
		complexity is introduced into	diversity can	curvilinear	n problem
		the multi-objective chemical	be maintained	fronts	n problem.
		reaction optimization algorithm	on the Pareto	noms.	
		reaction optimization argorithm.	on time 1 areto		
			and it can		
			converge to		
			the Pareto		
			optimal front.		
	PC	A new coding mechanism	The	The	Multi-
	RO [33]	is designed, the adaptive	improvement	computational	regional
		neighborhood structure	effect is better	complexity of	environme
		selection mechanism is	than the	the algorithm	ntal/econo
		embedded, the grid-based	comparative	is increased.	mic
		crowding distance strategy is	algorithms in		scheduling
		introduced and the kinetic	the three		ontimizatio
		anarou based search procedure	comparison		n problem
		energy-based search procedure	comparison		n problem.
		is developed.	indexes.		
	FM	The chemical reaction	It is	The	Analy
	IFS-	optimization algorithm is used	better than	training time	sis and
	RCCRO	for optimal cluster center	other methods	of the	modeling
	-FCM	generation for fuzzy clustering.	in terms of	algorithm is	of intrusion
	[34]		efficiency and	prolonged.	detection
			accuracy.		systems.

VII. FUSION OF CHEMICAL REACTION ALGORITHM WITH OTHER ALGORITHMS

The four elementary reactions in the chemical reaction optimization algorithm can well balance the local search ability and global search ability of the algorithm, and effectively avoid the algorithm from falling into local optimum. This makes the algorithm have the conditions and advantages to integrate with

other intelligent optimization algorithms. The improvements and applications of the chemical reaction optimization algorithm integrated with some other intelligent optimization algorithms are summarized below, as shown in TABLE II.

Intelli	Na	Fusion	Adva	Disadva	Applic
gent	me	Mechanism	ntage	ntage	ation
Algorithm					Scenario
Ant	CR	In the early stage of	It has	The	Traveli
Colony	ACA	ACO, CROA is used to	good	computationa	ng
Optimizati	[35]	generate the initial	convergen	l complexity	salesman
on (ACO)		feasible solution, and	ce	of the	problem.
		the feasible solution is	performan	algorithm is	
		transformed into the	ce, high	increased.	
		initial pheromone of	computati		
		ACO through the	onal		
		pheromone	efficiency		
		transformation strategy.	and good		
			generaliza		
			tion		
Doutiol		Introduce DDest	ability.	The best	7
e Swarm	RO-PS	and CRest to improve	rgence	results are not	/ benchmark
Ontimizati	O [36]	and <i>GDest</i> to improve	accuracy	obtained for	functions
on (PSO)	0[50]	operators modify	and	all functions	runetions.
		decomposition and	convergen	un functions.	
		synthesis criteria and	ce speed		
		add an end operator in	have been		
		the last iteration.	improved.		
	HB	The PSO equation	Impro	The	11
	CRO-B	is used as a	ve	applicability	benchmark
	PSO	neighborhood operator	classifier	of the	datasets.
	[37]	for collision reaction	performan	algorithm on	
		and exchange reaction.	ce while	ultra-high-di	
			reducing	mensional	
			the	datasets with	
			number of	a large	
			required	number of	
			teatures.	samples is not	
Lligher	CP	Apply CDOA to the	It has	vanuated.	0
order	O-HON	weight set training of	n nas high	applicability	0 henchmark
neural	N [38]	PSNN.	classificati	of the	datasets

TABLE II. Summary of advantages, disadvantages and applications of hybrid chemical reaction optimization algorithm

· 1					
network			on	algorithm in	
			accuracy	practical	
			and low	engineering	
			error rate.	problems is	
				not verified.	
	HO	CROA is improved	The	The	Realiza
	NN	by introducing a greedy	classificati	improvement	tion of
	training	process to update	on	in	ILI-MIL
	algorith	reactant molecules,	accuracy	classification	method;
	m based	which is then applied to	of the	accuracy is	multiple
	on	the training process of	algorithm	not	example
	chemica	PSNN.	has been	significant for	test Musk
	1		improved.	datasets with	dataset;
	reaction			smaller	image
	optimiz			training sets.	recognition
	ation			-	dataset.
	[39]				
Seque	ICR	Generate the initial	High	When the	Multi-t
ntial	OA [40]	feasible solution of	accuracy.	number of	уре
Insertion		CROA with SI.		workpieces is	workpiece
Algorithm				large, ICROA	processing
s (SI)				runs longer	robot
				than the	manufactur
				comparison	ing cell
				algorithm.	scheduling
				0	problem
					proorenn
Tabu	CR	Introduce elite	The	The	Flexibl
Tabu search	CR OTS	Introduce elite retention mechanism	The current	The improvement	Flexibl e job shop
Tabu search algorithm	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal	The improvement effect is not	Flexibl e job shop scheduling
Tabu search algorithm (TS)	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal solution	The improvement effect is not significantly	Flexibl e job shop scheduling problem.
Tabu search algorithm (TS)	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal solution for the	The improvement effect is not significantly better than	Flexibl e job shop scheduling problem.
Tabu search algorithm (TS)	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal solution for the case can	The improvement effect is not significantly better than the	Flexibl e job shop scheduling problem.
Tabu search algorithm (TS)	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal solution for the case can be	The improvement effect is not significantly better than the comparison	Flexibl e job shop scheduling problem.
Tabu search algorithm (TS)	CR OTS [41]	Introduce elite retention mechanism and tabu search.	The current optimal solution for the case can be obtained.	The improvement effect is not significantly better than the comparison algorithm.	Flexibl e job shop scheduling problem.
Tabu search algorithm (TS) Greed	CR OTS [41] GC	Introduce elite retention mechanism and tabu search. In the initial stage	The current optimal solution for the case can be obtained. The	The improvement effect is not significantly better than the comparison algorithm. The	Flexibl e job shop scheduling problem. Traveli
Tabu search algorithm (TS) Greed	CR OTS [41] GC RO [42]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy	The current optimal solution for the case can be obtained. The quality of	The improvement effect is not significantly better than the comparison algorithm. The algorithm	Flexibl e job shop scheduling problem. Traveli ng
Tabu search algorithm (TS) Greed y Algorithm	CR OTS [41] GC RO [42]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced	The current optimal solution for the case can be obtained. The quality of the	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer.	Flexibl e job shop scheduling problem. Traveli ng salesman
Tabu search algorithm (TS) Greed y Algorithm	CR OTS [41] GC RO [42]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial	The current optimal solution for the case can be obtained. The quality of the solution is	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer.	Flexibl e job shop scheduling problem. Traveli ng salesman problem.
Tabu search algorithm (TS) Greed y Algorithm	CR OTS [41] GC RO [42]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population.	The current optimal solution for the case can be obtained. The quality of the solution is improved.	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer.	Flexibl e job shop scheduling problem. Traveli ng salesman problem.
Tabu search algorithm (TS) Greed y Algorithm Water	CR OTS [41] GC RO [42] WC	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains	The current optimal solution for the case can be obtained. The quality of the solution is improved. The	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer.	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa
Tabu search algorithm (TS) Greed y Algorithm Water Wave	CR OTS [41] GC RO [42] WC RO [43]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains the collision reaction	The current optimal solution for the case can be obtained. The quality of the solution is improved. The optimizati	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer.	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa cement
Tabu search algorithm (TS) Greed y Algorithm Water Wave Optimizati	CR OTS [41] GC RO [42] WC RO [43]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains the collision reaction and exchange reaction	The current optimal solution for the case can be obtained. The quality of the solution is improved. The optimizati on	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer. The overall complexity of	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa cement flow shop
Tabu search algorithm (TS) Greed y Algorithm Water Wave Optimizati on	CR OTS [41] GC RO [42] WC RO [43]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains the collision reaction and exchange reaction to optimize the	The current optimal solution for the case can be obtained. The quality of the solution is improved. The optimizati on performan	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer. The overall complexity of the algorithm	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa cement flow shop scheduling
Tabu search algorithm (TS) Greed y Algorithm Water Wave Optimizati on Algorithm	CR OTS [41] GC RO [42] WC RO [43]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains the collision reaction and exchange reaction to optimize the individual population.	The current optimal solution for the case can be obtained. The quality of the solution is improved. The optimizati on performan ce is	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer. The overall complexity of the algorithm increases.	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa cement flow shop scheduling problem.
Tabu search algorithm (TS) Greed y Algorithm Water Wave Optimizati on Algorithm (WWO)	CR OTS [41] GC RO [42] WC RO [43]	Introduce elite retention mechanism and tabu search. In the initial stage of CROA, the greedy algorithm is introduced to generate good initial molecular population. CROA only retains the collision reaction and exchange reaction to optimize the individual population, and WWO reconstructs	The current optimal solution for the case can be obtained. The quality of the solution is improved. The optimizati on performan ce is better.	The improvement effect is not significantly better than the comparison algorithm. The algorithm runs longer. The overall complexity of the algorithm increases.	Flexibl e job shop scheduling problem. Traveli ng salesman problem. Displa cement flow shop scheduling problem.

		operation, the refraction			
		operation, and the			
		breaking wave			
		operation to optimize			
		the overall population.			
Artific	AB	Use ABC to	Highe	Converge	Identifi
ial Bee	-CRO	generate the position of	r solution	nce is slower	cation and
Colony	[44]	the initial population,	accuracy	than the ABC	classificati
Algorithm		and then use CROA to	can be	algorithm.	on of
s (ABC)		update the current	achieved.		optimal
		position of the			feature
		population in the search			subsets;
		space.			medical
		-			diagnosis

VIII. BRIEF REVIEW

As a new meta-heuristic intelligent optimization algorithm, chemical reaction optimization algorithm has attracted much attention since it was proposed, and has gradually become an important research topic. The transformation and transfer of energy in different entities and forms make chemical reaction optimization algorithm unique among intelligent algorithms. The canonical version and the real-encoded version of the algorithm make the algorithm capable of solving both discrete and continuous problems. The flexibility and ease of implementation of the algorithm design enable the chemical reaction optimization algorithm to be well integrated with other algorithms, while also having the potential to solve those problems that have not been solved by other intelligent algorithms. Through continuous research and development, the chemical reaction optimization algorithm has been widely used in various fields, and its improvement and application research for different practical problems is also deepening.

Compared with other classical intelligent optimization algorithms, the research time of chemical reaction optimization algorithm is still short. Although various improvement strategies and algorithm fusion have improved the solution performance of the algorithm to a certain extent, there are still areas that need to be improved and long-term concentrated research is required. (1) Theoretical research on CROA. The theoretical research of the algorithm is still on the proof of global convergence, and the theoretical research on other aspects of stability, complexity and the main factors affecting the performance also needs to be further promoted. In addition, the parameter settings of the algorithm often have a great impact on the overall performance of the algorithm. At present, the parameter selection of CROA is still based on experience or experimental design, and depends on specific problems. Therefore, it is also necessary to study the specific setting of parameters theoretically, and analyze whether it has the universal parameter combination that does not require precise adjustment. (2) Research on CROA application. Chemical reaction optimization algorithm has been widely used in various fields, and improved applications for specific problems have emerged in an endless stream, but there are still defects. There is still a lot of research space on how to make the theoretical problems solved as close to reality as possible and obtain the optimal solution. At present, CROA is mostly used to solve single-objective optimization problems,

and there are few applied researches on multi-objective, multi-dimensional, dynamic uncertainty, etc., which need to be further promoted. (3) Research on CROA improvement. The characteristics of the four primary reactions in the chemical reaction optimization algorithm make the algorithm have good global convergence. Among them, decomposition reaction and synthesis reaction operations can be widely considered to be combined with other algorithms that are easy to fall into local optimum, so as to help other algorithms improve population diversity and jump out of local optimum. However, there are few improvement studies on the insufficient utilization of feedback information in the solution process of CROA. It is also worth considering how to avoid the algorithm from easily falling into redundant iterations during the solution process, especially in the later stage of the solution, and to improve the efficiency of the solution.

IX. CONCLUSION

The characteristics and advantages of the chemical reaction optimization algorithm make it have a very broad application research prospect. How to improve it to meet the specific practical problems is the research focus. On the basis of explaining the principle of chemical reaction optimization algorithm and related theories, this paper introduces the application and research of the algorithm in different fields in recent years. The improvement and application of chemical reaction optimization algorithm are reviewed from the aspects of algorithm design framework, molecular structure, operation operator and algorithm fusion. Finally, the algorithm is summarized and the prospect of future development is made to provide guidance and reference for the follow-up research.

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