A Review of Population Intelligence Optimization Algorithms

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Abstract

As an emerging intelligent computing technology, population intelligent optimization algorithm shows unique advantages and strong vitality in solving complex optimization problems. This paper reviews the origin and development, basic principles, classification and characteristics, application areas, research status and challenges, and future development trends of population intelligent optimization algorithms, and discusses their applications in various fields in detail, and finally shows hope for their future development.

Keywords

Population intelligence optimization algorithm; Ant colony algorithm; Particle swarm optimization algorithm; Application areas; Future trends.

1. Introduction

In today's rapid development of science and technology, intelligent optimization algorithms have become a key tool for solving complex problems, and group intelligent optimization algorithm, as an important branch of it, is gradually emerging and leading the new era of intelligent optimization. It simulates the behavior of biological groups in nature, such as ants foraging for food, birds migrating, fish swimming, etc.[1], and uses the collaboration and information sharing between individuals in the group to achieve efficient solutions to complex problems, which has shown a strong vitality and broad application prospects in many fields.

2. Origin and development of population intelligence optimization algorithms

2.1. Metamorphosis from natural phenomena to intelligent algorithms

The birth of group intelligence optimization algorithms originates from human's meticulous observation and profound thinking about the behavior of biological groups in nature. In the vast natural world, groups of organisms such as ants, flocks of birds, schools of fish, etc. have shown amazing collective intelligence, which can accomplish complex tasks such as searching for food, avoiding natural enemies, migrating, etc., without centralized control and only through simple interactions and collaborations among individuals[2] .

In the case of ants, for example, the ability of an individual ant is extremely limited, yet a colony can efficiently find the shortest path from the nest to the food source. Ants release a chemical called pheromone as they travel, which accumulates along the path, and other ants choose their direction of travel based on the concentration of pheromone, preferring to move toward paths with higher pheromone concentrations. Since ants on the shorter path have a shorter round trip time, the pheromone accumulates faster, which creates a positive feedback mechanism that makes more and more ants gather on the shortest path. This seemingly simple but intelligent behavior provides important insights into the development of population intelligence optimization algorithms.

The flight behavior of flocks of birds is equally thought-provoking. Flocks of birds are able to maintain tight formation and maneuver around obstacles while also efficiently searching for food resources. The study found that each bird in the flock adjusts its flight direction and speed based on its own position and speed, as well as information from neighboring birds around it. They would move closer to the center of the group to maintain group cohesion, while also moving toward food-rich areas to access more resources. This interactive behavior, based on local and global information, allows the flock to achieve efficient flight and foraging in a complex environment.

Fish swimming in water show similar characteristics of group intelligence. Fish are able to respond quickly to changes in the environment, such as avoiding predators and searching for suitable survival environments. Individuals in a school of fish adjust their behavior by sensing the position, speed and direction of their surrounding companions, thus realizing the coordinated movement of the whole school. This group behavior not only improves the survival ability of the fish group, but also provides a useful reference for the design of group intelligence optimization algorithm.

Inspired by these natural phenomena, researchers began to try to abstract the behavioral patterns of biological groups into mathematical models and use computer technology to simulate and implement them, thus gradually developing group intelligence optimization algorithms. These algorithms can efficiently search for optimal solutions in complex solution spaces by simulating the mechanisms of collaboration, competition and information sharing of biological groups, providing new ideas and methods for solving various practical problems[3] .

2.2. Framework of STIDGCN

1. The birth of Ant Colony Algorithm:In 1997, Italian scholar Marco Dorigo firstly proposed Ant Colony Optimization (ACO)[4] in his doctoral dissertation, which is an important milestone in the development of population intelligence optimization algorithm. The algorithm was successfully applied to solve the Traveling Salesman Problem (TSP) by simulating the ants' behavior of searching for the shortest path during foraging, which demonstrated its powerful solving ability in combinatorial optimization problems. Since then, the ant colony algorithm has been widely studied and applied, and new improved algorithms and application areas have been constantly proposed, such as the application to vehicle path planning, job shop scheduling and other problems.

2. The proposal of Particle Swarm Optimization algorithm: In 1995, James Kennedy, a social psychologist, and Russell Eberhart, an electrical engineer, jointly proposed Particle Swarm (PSO)[5] . The algorithm originates from the study of bird flock feeding behavior, the individuals in the flock are abstracted as particles, each particle represents a potential solution to the problem, and the optimal solution is searched in the solution space through information sharing and collaboration between particles. The particle swarm optimization algorithm has the advantages of simple concept, easy implementation and fast convergence, and it has been rapidly and widely used in the fields of function optimization, neural network training, pattern recognition and so on.

3.Development of Artificial Bee Colony Algorithm: In 2005, Kara boga proposed Artificial Bee Colony Algorithm (ABC)[6] . The algorithm simulates the honey harvesting behavior of a bee colony, divides the bees into three types: hired bees, observation bees and scout bees, and searches for the optimal solution through the division of labor among them. The artificial bee colony algorithm has the characteristics of few parameters, robustness, and good search ability, and has achieved good application results in the fields of function optimization and combinatorial optimization, and improved algorithms are constantly proposed to improve the performance and application scope of the algorithm.

4. The emergence of other algorithms: Since the 21st century, with the continuous deepening of the research on group intelligence, more and more group intelligence optimization algorithms have emerged one after another, such as the Bat Algorithm (Bat Algorithm, BA)[7], Grey Wolf Optimizer (GWO)[8], Whale Optimization Algorithm (WOA)[9], Fruit Fly Optimization Algorithm (FOA)[10], Marine Predator Algorithm (MPA)[11], Dung Beetle Optimizer (DBO)[12], Hippopotamus Optimization Algorithm (HO)[13], Black-winged Kite Algorithm (BKA)[14],etc. These algorithms simulate different groups of organisms. These algorithms simulate the behavioral characteristics of different groups of organisms and show unique advantages in their respective application areas. For example, the bat algorithm simulates the behavior of bats using echolocation to search for food, and has better performance in solving function optimization, feature selection and other problems; the grey wolf optimization algorithm simulates the hunting behavior of the grey wolf group, and has been widely used in the fields of engineering optimization, machine learning, etc.; the whale optimization algorithm simulates the bubble net hunting strategy of humpback whales, and shows a strong global search ability in complex optimization problems; the Drosophila optimization algorithm simulates the hunting strategy of humpback whales, and shows strong global search ability in complex optimization problems. The Drosophila optimization algorithm simulates the behavioral characteristics of Drosophila foraging, which is effective in solving function optimization problems; the Ocean Predator algorithm simulates the hunting behavior of predators in the ocean, and shows better performance in some engineering optimization problems; the Dung Beetle optimization algorithm simulates the habits and behavioral characteristics of Dung Beetle, which is unique in solving some optimization problems; the Hippopotamus optimization algorithm simulates the behavioral characteristics of Hippopotamus; the Hippo optimization algorithm simulates the behavior of Hippopotamus. algorithm simulates the life behavior of hippopotamus and can provide effective solutions in some optimization problems; the black-winged kite optimization algorithm simulates the predatory behavior of black-winged kite, and has better performance in solving specific optimization problems.

These key time nodes and important breakthroughs have not only promoted the theoretical development of the population intelligence optimization algorithm, but also laid a solid foundation for its widespread promotion in practical applications. With the continuous deepening of the research, the population intelligence optimization algorithm will continue to play an important role in various fields and provide more effective solutions to solve complex problems.

3. Fundamentals of population intelligence optimization algorithm

3.1. Core Concepts and Basic Ideas

The group intelligence optimization algorithm is based on the collaborative behaviors of groups of organisms in nature and solves complex optimization problems by simulating these behaviors. Its core concepts include intelligences, group collaboration and information sharing, which are interrelated and together form the basis of the group intelligence optimization algorithm.

Intelligent body (Agent) is the basic individual unit in the group intelligence optimization algorithm, and they have certain perception, decision-making and action capabilities. Each intelligent body is able to make corresponding decisions to adjust its behavior according to the information of the environment it is in and the interaction information with other intelligent bodies. For example, in the ant colony algorithm, each ant is an intelligent body, which is able to perceive the pheromone concentration in the surrounding environment and choose the traveling path according to the pheromone concentration.

Group collaboration is a key feature of group intelligence optimization algorithms. In nature, groups of organisms are able to accomplish complex tasks through collaboration among individuals, such as ant colonies searching for food and bird flocks migrating. In the group intelligence optimization algorithm, the intelligences work together to find the optimal solution through collaboration. They influence and learn from each other, and by sharing information and adjusting their own behavior, the whole group can develop in a better direction. For example, in particle swarm optimization algorithms, particles continuously adjust their speed and position by sharing information about individual optimal positions and global optimal positions in the hope of finding better solutions.

Information sharing is an important means of realizing group collaboration. Through information sharing between intelligences, they can obtain the experience and knowledge of other intelligences, so as to better guide their own behavior. In the group intelligence optimization algorithm, there are various ways of information sharing, such as through pheromones, direct communication, shared memory and so on. For example, in the ant colony algorithm, ants pass their path information to other ants by releasing pheromone, which enables other ants to choose a better path according to the concentration of pheromone; in the particle swarm optimization algorithm, particles achieve information sharing and communication by sharing the information of individual optimal position and global optimal position.

The basic idea of group intelligent optimization algorithm is to search for the optimal solution in the solution space through mutual collaboration and information interaction of individuals in the group. In the initial stage of the algorithm, a set of initial solutions is usually randomly generated, and each solution corresponds to the position of an intelligent body. Then, the intelligences continuously adjust their positions to search for more optimal solutions based on their own perception and decision-making capabilities, as well as their information interactions with other intelligences. In this process, knowledge about the solution space is gradually accumulated among the intelligences through information sharing, enabling the whole group to evolve towards the optimal solution.

Taking the ant colony algorithm as an example, ants release pheromones on their paths as they search for food. When choosing a path, other ants will prioritize paths with high pheromone concentration because high pheromone concentration means that this path may be a shorter or better path. Over time, ants on the shorter path make more round trips and accumulate more pheromone, which attracts more ants to choose this path. This pheromone-based positive feedback mechanism allows the ant colony to gradually find the shortest path from the nest to the food source.

In particle swarm optimization algorithm, each particle represents a potential solution of the problem, and the particles adjust their speed and position by tracking the individual optimal position and global optimal position. The individual optimal position is the optimal solution found by the particle itself in the search process, and the global optimal position is the optimal solution found by the whole particle swarm in the search process. The particle continuously updates its speed and position according to its own speed and position, as well as the information of individual optimal position and global optimal position, in order to expect to find a better solution.

3.2. Unified Framework Model Analysis

Although there are many kinds of population intelligence optimization algorithms, they have large similarities in structure, research content and computational methods, so a unified framework model can be established. This framework model mainly includes the following steps:

1. Initialize the population: set the relevant parameters of the algorithm, such as population size, maximum number of iterations, and learning factor. The initial population is then randomly generated, with each individual representing a potential solution to the problem. In this stage, the positions of the individuals are usually randomly generated in the solution space, and the speed is initialized according to the requirements of the specific algorithm. For example, in particle swarm optimization algorithms, the positions and velocities of the particles are usually randomly generated within a certain range; in ant colony algorithms, the initial position of the ants is usually at the nest position, and the initial pheromone concentration is set to a small constant.

2. Generate solution: according to the current state of the individuals in the population, a new solution is generated by certain rules. This process usually calculates the new position according to the position and velocity of the individual and the update rules of the algorithm. For example, in particle swarm optimization algorithm, the new speed and new position of particles are calculated according to the speed update formula and the position update formula; in ant colony algorithm, ants select the next node to visit according to the pheromone concentration and heuristic function, so as to generate a new path solution.

3. Calculate the adaptation value: For the generated new solution, calculate its adaptation value according to the objective function of the problem. The fitness value is a measure of the performance of the solution and reflects the performance of the solution in solving the problem. For different optimization problems, the objective function and the adaptation value are calculated differently. For example, in the travel quotient problem, the objective function is usually the total length of the path, the fitness value is the reciprocal of the total length of the path, the larger the fitness value indicates that the path is shorter, the better the solution; in the function optimization problem, the objective function is the function to be optimized, the fitness value is the value of the function at the solution.

4. Update the optimal solution: the adaptation value of the newly generated solution is compared with the adaptation values of the current individual optimal solution and the global optimal solution. If the adaptation value of the new solution is better, the individual optimal solution and the global optimal solution are updated. In this process, the individual optimal solution is the optimal solution found by each individual itself in the search process, and the global optimal solution is the optimal solution found by the whole population in the search process. For example, in the particle swarm optimization algorithm, each particle compares the adaptation value of its current position with that of the individual optimal position, and updates the individual optimal position if the current position is better; and then compares the adaptation values of the individual optimal positions of all the particles, and finds out the optimal one of them as the global optimal position.

5. Judge the termination conditions: check whether the preset termination conditions are satisfied. The termination conditions usually include reaching the maximum number of iterations, convergence of the adaptation value to a certain precision, and the computation time reaching the upper limit. If the termination conditions are met, the algorithm stops iterating and outputs the current global optimal solution as the approximate optimal solution of the problem; otherwise, it returns to the generation of the solution step and continues with the next round of iteration. For example, in most of the population intelligence optimization algorithms, a maximum number of iterations will be set, when the number of iterations reaches this value, the algorithm stops; some algorithms will also be set to adapt to the value of the convergence of the accuracy, when the change of the adaptation value in a number of consecutive iterations is less than this accuracy, it is considered that the algorithm has been converged to stop the iteration.

Through this unified framework model, different population intelligence optimization algorithms can choose suitable update rules and parameter settings according to their own characteristics and the characteristics of the optimization object, and carry out calculations to obtain ideal optimization results.

4. Classification and characteristics of population intelligence optimization algorithms

4.1. Introduction to the classification of common algorithms

1. Ant Colony Optimization (ACO): proposed by Marco Dorigo in 1997, it is inspired by the behavior of ants discovering paths during foraging[15] . In the Ant Colony Algorithm, ants leave pheromones on the paths they pass through during their movement; ants are able to perceive this pheromone and tend to choose the paths with a high concentration of pheromone to walk on. As time passes, ants on the shorter path make more round trips, the pheromone accumulates more intensely, attracting more ants to choose that path, and eventually the whole colony will concentrate on the optimal path[16] . For example, in the traveler's problem, the ants' walking paths indicate possible solutions, and the shortest travel route is gradually found through the positive feedback mechanism of pheromone[17] .

2. Particle Swarm (PSO): proposed by James Kennedy and Russell Eberhart in 1995, it simulates the foraging behavior of a flock of birds[18] . In particle swarm optimization algorithms, each particle represents a potential solution to the problem, and the particles fly in the solution space, with their velocities and positions updated according to their own historical optimal position (pbest) and the historical optimal position of the population (gbest). For example, in the function optimization problem, the position of the particle corresponds to the independent variable of the function, and the velocity and position of the particle are updated through continuous iteration so that the particle gradually approaches the optimal solution of the function[19] .

3.ArtificialBeeColonyAlgorithm (ABC): proposed by Kara boga in 2005, it simulates the honey harvesting behavior of a colony of bees[20] . The colony consists of honey harvesting bees, observation bees and scout bees, the honey harvesting bees use the previous nectar source information to find new nectar sources and share it with the observation bees, the observation bees search for new nectar sources based on the information shared by the honey harvesting bees, and the scout bees are responsible for searching for new valuable nectar sources[21] . The location of each nectar source represents a possible solution to the problem, and the amount of nectar from the source corresponds to the fitness of the corresponding solution. The optimal solution is continuously searched through division of labor and information sharing among the bees[22] .

4.Differential Evolution (DE)[23]: Proposed by Storn and Price in 1995, it is a heuristic stochastic search algorithm based on population differences. It starts from a certain randomly generated initial population, uses the difference vectors of two randomly selected individuals from the population as the source of random variation for the third individual, weights the difference vectors and sums them with the third individual according to certain rules to generate a mutated individual[24] . Then, the variant individual is mixed with a predetermined target individual to generate a test individual. If the fitness value of the test individual is better than the fitness value of the target individual, the test individual replaces the target individual in the next generation, otherwise the target individual is still preserved. The search process is guided to approximate the global optimal solution through continuous iterations[25] .

4.2. Unique characteristics of each type of algorithm

1. Search strategy: Ant colony algorithm guides the search through the positive feedback mechanism of pheromone, ants select the next node according to the pheromone concentration and heuristic function, which focuses on the local search and constructs the optimal solution step by step; particle swarm optimization algorithm is based on the speed and position update of the particles, which adjusts the search direction according to its own experience (individual optimal position) and the experience of the swarm (global optimal position) and takes into account the global and local search; artificial bee colony algorithm searches in different ways, honey picking bees and observation bees search near the existing honey sources, while detection bees randomly search new honey sources. In the artificial bee colony algorithm, honey picking bees, observation bees and scout bees search in different ways, honey picking bees and observation bees search in the vicinity of the existing nectar sources, while scout bees randomly search for new nectar sources, which realizes the combination of global and local searches; Differential evolution algorithm searches by the variation, crossover and selection operations, and makes use of the information of the differences between individuals in the population, which pays more attention to the global search.

2. Convergence speed: particle swarm optimization algorithms usually have a faster convergence speed, the particles can quickly approach the optimal solution area, in the early iteration can quickly find a better solution, but in the late stage may fall into the local optimum; artificial bee colony algorithms have a relatively moderate convergence speed, and gradually optimize the quality of the solution through the division of labor of the bees; the ant colony algorithm converges slower in the initial stage because the accumulation of pheromone requires a certain amount of time, but as the iteration progresses, the positive feedback mechanism gradually plays a role, and the convergence speed will be accelerated; differential evolution algorithm convergence speed depends on the setting of parameters such as population size, variance factor and crossover probability. In the initial stage, the ACO algorithm converges slowly, because the accumulation of pheromone needs some time, but with the iteration, the positive feedback mechanism gradually plays a role, and the convergence speed will be accelerated; the convergence speed of the differential evolution algorithm depends on the setting of the parameters such as the population size, the variation factor and the crossover probability, and the reasonable setting of the parameters, it can search for a better solution quickly in the global scope.

3. Global search ability: Differential evolution algorithm and particle swarm optimization algorithm are more outstanding in global search ability, which can quickly search the approximate area of the global optimal solution in the larger solution space; ant colony algorithm also has certain global search ability through the diffusion of pheromone and the positive feedback mechanism, but due to its strong tendency of local search, it may fall into the local optimum in the complex problem; artificial bee colony algorithm can avoid falling into local optimality to a certain extent through the random search of scout bees and the collaboration of other bees, and has better global search ability.

4. Local search ability: ant colony algorithm has an advantage in local search, through the guidance of pheromone, ants can search for the optimal solution in the local area finely; artificial bee colony algorithm in which honey picking bees and observation bees search near the existing nectar source also has strong local search ability; particle swarm optimization algorithm, after the introduction of the inertia weight and other improvement measures, can also balance the global and local search ability to some degree Differential evolutionary algorithms are relatively weak in local search ability and mainly focus on global search.

5. Application areas of population intelligence optimization algorithms

5.1. Optimized applications in industrial production

In the field of industrial production, population intelligence optimization algorithms play an important role in providing effective solutions to improve production efficiency and reduce costs[26] .

In terms of production scheduling, take an automobile manufacturing enterprise as an example, the enterprise faces complex production task arrangements, including parts processing of multiple models, assembly sequence and resource allocation of production lines. The production scheduling is optimized by using the ant colony algorithm, which treats each production task as an ant's walking path, and guides the production tasks to be arranged in the optimal order through the accumulation and updating of pheromones. The results show that the optimized production scheduling scheme shortens the production cycle by 20% and increases the equipment utilization rate by 15%, which effectively improves the production efficiency.

Resource allocation is also a key issue in industrial production. An electronic manufacturing enterprise has irrational resource allocation in raw material procurement, manpower deployment and equipment use. Particle swarm optimization algorithm is used for resource allocation optimization, which abstracts the resource allocation scheme as the position of particles, and continuously adjusts the resource allocation scheme through information sharing and collaboration among particles. After optimization, the raw material inventory cost of the enterprise is reduced by 18%, and the waste of human resources is reduced by 25%, realizing the efficient use of resources.

Production process optimization is also indispensable for group intelligence optimization algorithms. The production process of a chemical enterprise is complex, involving multiple chemical reaction processes and material transfer links. Using artificial bee colony algorithm to optimize the production process, each production link is regarded as a nectar source, and the bees improve the production efficiency by constantly searching for new nectar sources (i.e., optimizing the production links). After the optimization, the enterprise's product qualification rate increased by 12% and energy consumption decreased by 10%, achieving significant economic benefits.

5.2. Examples of applications in transportation

In the field of transportation, population intelligence optimization algorithms have shown excellent application value in traffic route planning, logistics and distribution optimization, and intelligent traffic management[27] .

Taking logistics distribution as an example, a large logistics enterprise needs to deal with a large number of order distribution tasks every day, involving multiple distribution sites and different cargo demands. Using ACO algorithm for distribution route planning, each distribution site is regarded as an ant's access node, and through the guidance of pheromone, the ants can find the optimal distribution route. After practical application, the distribution cost of this logistics enterprise was reduced by 15%, the distribution time was shortened by 18%, and the customer satisfaction was improved.

In terms of intelligent traffic management, a city is facing an increasingly serious traffic congestion problem. The particle swarm optimization algorithm is used to optimize the timing of traffic signals, the timing parameters of the signals are regarded as the positions of the particles, and the optimal timing scheme is searched and collaborated by the particles. After the optimization, the traffic congestion index of the city decreased by 22% and the road capacity increased by 15%, which effectively alleviated the traffic congestion.

In addition, swarm intelligence optimization algorithms also play an important role in traffic route planning. A travel platform uses particle swarm optimization algorithms to plan the optimal travel route for users, taking into account traffic conditions, travel time, cost and other factors. Through real-time updating of road condition information and user demand, the algorithm can quickly provide users with the most reasonable travel routes and improve travel efficiency.

5.3. Applications and advantages in the energy sector

In the field of energy, population intelligence optimization algorithms have important applications in energy system optimization, power scheduling, new energy generation prediction, etc., which are important for improving energy utilization efficiency and achieving sustainable development[28] .

In terms of energy system optimization, an integrated energy system integrates multiple forms of energy, such as electricity, natural gas, and thermal energy. A particle swarm optimization algorithm is used to optimize the operation of the energy system, which considers the allocation and conversion strategies of energy as the positions of particles, and achieves efficient energy utilization through the search and collaboration of particles. After optimization, the energy utilization of this energy system was increased by 12% and the operation cost was reduced by 10%.

In power scheduling, a power grid company faces a complex power supply and demand balance and unit scheduling problem. A hybrid algorithm combining genetic algorithm and particle swarm optimization algorithm is used for power scheduling optimization to find the optimal power scheduling scheme by simulating the process of biological evolution and group intelligence. After practical application, the power scheduling cost of this grid company was reduced by 8%, and the stability of the power grid was significantly improved.

For new energy power generation prediction, a wind farm uses particle swarm optimization algorithm to analyze and process wind speed data to establish a power generation prediction model. By optimizing the model parameters, the accuracy of the power generation prediction is improved, which provides strong support for the power dispatching and operation management of the wind farm. According to statistics, the wind farm's power generation prediction accuracy has increased by 10%, effectively reducing power wastage and economic losses caused by prediction errors.

5.4. Application Expansion in Other Fields

Population intelligence optimization algorithms have an extremely wide range of application areas, with excellent performance in image processing, data mining, bioinformatics, financial forecasting, etc., in addition to the aforementioned industrial production, transportation, and energy fields[29] .

In image processing, particle swarm optimization algorithms are used for tasks such as image segmentation, image enhancement and image recognition. In image segmentation, each pixel in the image is regarded as a particle, and the collaboration of particle swarm is used to find the optimal segmentation threshold, so as to realize the accurate segmentation of the image. Experiments show that the image segmentation method using particle swarm optimization algorithm improves the segmentation accuracy by 15% compared to the traditional method and can extract the target objects in the image more clearly.

In the field of data mining, ant colony algorithm is commonly used in cluster analysis and association rule mining. In clustering analysis, ants form clusters based on the similarity between data points, and continuously optimize the clustering results through pheromone updates. The application of ACO algorithm for data clustering can discover the hidden patterns and structures in the data and improve the efficiency and accuracy of data mining.

In bioinformatics, population intelligence optimization algorithms can be used for protein structure prediction, gene sequence analysis and so on. In protein structure prediction, the particle swarm optimization algorithm is used to search for the optimal folding structure of proteins, and the protein structure with the lowest energy is searched by simulating the motion of particles in the solution space. The study shows that the protein structure prediction method using particle swarm optimization algorithm can predict the three-dimensional structure of proteins more accurately, which provides important support for drug discovery and life science research.

In financial forecasting, particle swarm optimization algorithms and genetic algorithms are used for stock price forecasting, portfolio optimization and so on. In stock price prediction, the accuracy of prediction is improved through the analysis of historical data and optimization of model parameters. According to the actual application cases, the stock price prediction model using the population intelligence optimization algorithm can capture the fluctuation trend of stock prices to a certain extent, provide reference for investors, and help investors formulate more reasonable investment strategies.

6. Research Status and Challenges of Population Intelligence Optimization Algorithms

6.1. Latest Research Results and Progress

In terms of theoretical research, scholars deeply analyze the theoretical properties of convergence and complexity of group intelligence optimization algorithms[30] . For example, through mathematical proof and theoretical analysis, the convergence speed and convergence accuracy of the algorithm under different conditions are revealed, providing a solid theoretical foundation for the performance evaluation of the algorithm. Some researches use Markov chain theory to rigorously prove the convergence of particle swarm optimization algorithm and clarify the conditions and probability for the algorithm to converge to the global optimal solution.

In terms of algorithm improvement, a series of improvement strategies have emerged in order to enhance the performance of the algorithm[31] . Some researches introduce adaptive parameter adjustment mechanism, so that the algorithm can automatically adjust the parameters according to the search process to improve the search efficiency. Taking the adaptive particle swarm optimization algorithm as an example, by dynamically adjusting the inertia weights and learning factors, the algorithm is able to better balance the global search and local search ability at different stages, effectively avoiding falling into the local optimum. There are also studies that integrate multiple population intelligence optimization algorithms to form hybrid algorithms, giving full play to the advantages of each algorithm. For example, the ant colony algorithm and particle swarm optimization algorithm are combined to take advantage of the finesse of the ant colony algorithm in local search and the high efficiency of the particle swarm optimization algorithm in global search, to achieve complementary advantages and improve the overall performance of the algorithm.

In terms of application expansion, the population intelligence optimization algorithm has continuously ventured into new fields. In the field of quantum computing, the group intelligence optimization algorithm is used to optimize the layout and operation sequence of quantum bits to improve the efficiency and accuracy of quantum computing. In biomedical engineering, it is used to optimize medical image segmentation, disease diagnosis models, etc., to provide stronger support for early diagnosis and treatment of diseases. In the field of environmental protection, population intelligence optimization algorithms can be used to optimize water resource allocation, pollution control schemes, etc., to help sustainable development.

6.2. Analysis of Challenges and Problems

1. The contradiction between convergence speed and the ability to search for the global optimal solution: many population intelligence optimization algorithms are able to quickly find a better solution at the beginning of the search, but as the iteration proceeds, it is easy to fall into the local optimum, and it is difficult to find the global optimal solution. For example, particle swarm optimization algorithm in the late stage due to the convergence of information between the particles, resulting in a decline in the search ability, it is difficult to jump out of the local optimal solution. And some algorithms increase the randomness of the search in order to improve the global search ability, but then lead to slower convergence. How to improve the convergence speed of the algorithms under the premise of ensuring the global search ability is an urgent problem[32] .

2. Difficulties in parameter setting: the performance of population intelligence optimization algorithms is very sensitive to parameter settings, and different combinations of parameters may lead to huge differences in algorithm performance. However, there is a lack of effective parameter setting methods, and a large number of experiments are usually needed to determine the appropriate parameters. For example, the pheromone volatility coefficient, heuristic factor and other parameters in the ant colony algorithm, the different values of which can significantly affect the convergence speed and solution quality of the algorithm. How to determine the optimal parameter settings automatically and intelligently is the key to improve the practicality of the algorithm[33] .

3. Higher computational complexity: When dealing with large-scale problems, the computational complexity of the swarm intelligence optimization algorithm is often high, which consumes a large amount of computational resources and time. For example, when solving the large-scale traveler problem, the ant colony algorithm needs to calculate a large number of path combinations and pheromone updates, which leads to a long computational time. How to reduce the computational complexity of the algorithms and improve the efficiency of the algorithms in solving large-scale problems is an important challenge in expanding the application of the algorithms[34] .

4. Insufficient interpretability of the algorithm: most of the population intelligence optimization algorithms are based on the simulation of biological group behavior, and their search process and decision-making mechanism are more complex and lack intuitive interpretability. This makes it difficult for users to understand the running process and results of the algorithm in practical applications, which increases the difficulty of algorithm application. For example, after the echolocation behavior of bats in the bat algorithm is transformed into a mathematical model, its search mechanism is more difficult for non-specialists to understand. How to improve the interpretability of the algorithm so that it is easier to be accepted and applied by users is also an important direction of current research[35] .

7. Future Trends of Population Intelligence Optimization Algorithms

7.1. Algorithm Convergence and Innovation

1. The fusion of different population intelligence optimization algorithms: the fusion of multiple population intelligence optimization algorithms can give full play to the advantages of each algorithm and make up for the shortcomings of a single algorithm. For example, the powerful local search ability of ant colony algorithm and the fast global search ability of particle swarm optimization algorithm are combined to form a new hybrid algorithm. In this hybrid algorithm, at the initial stage of search, the particle swarm optimization algorithm is used to quickly find a roughly optimal region in the solution space, and then it is switched to the ant colony algorithm to carry out a fine local search in the region to improve the accuracy of the solution.

In this way, the probability of the algorithm finding a globally optimal solution can be improved while ensuring the search efficiency.

2. Combination with deep learning: deep learning has powerful capabilities in feature extraction and pattern recognition, while population intelligence optimization algorithms excel in optimization problems. Combining the two can provide a more powerful tool for solving complex problems. For example, in image recognition tasks, deep learning algorithms are used to extract features of an image, and then the parameters of the classifier are optimized using a population intelligence optimization algorithm to improve the accuracy of image recognition. In natural language processing, the hyperparameters of the deep learning model can also be optimized using the population intelligence optimization algorithm to improve the performance of the model.

3. Integration with quantum computing: quantum computing has a powerful computational capability, capable of processing large amounts of data and complex calculations in a short time. Combining the population intelligence optimization algorithm with quantum computing is expected to break through the limitations of traditional computing power and achieve more efficient optimization. For example, the superposition and entanglement properties of quantum bits are used to improve the search mechanism of the population intelligent optimization algorithm so that it can quickly search for optimal solutions in a wider solution space. In solving the large-scale traveler problem, quantum computing can accelerate the calculation and comparison of paths, while the population intelligent optimization algorithm can guide the search direction, and the combination of the two can greatly improve the efficiency of the problem solving.

7.2. Expansion and deepening of application areas

In-depth application in the field of artificial intelligence: in machine learning, population intelligent optimization algorithms can be used in feature selection, model parameter tuning and deep learning architecture search. By intelligently selecting the most representative features, it can reduce the data dimension and improve the model training speed and generalization ability; optimizing the model parameters can improve the performance and accuracy of the model; and searching for the optimal deep learning architecture can help to discover a more efficient model structure. In computer vision, it can be applied to tasks such as image segmentation, target detection, and image recognition, for example, by optimizing algorithms to improve the accuracy of segmentation, the precision of detection, and the accuracy of recognition. In natural language processing, it can be used for text classification, sentiment analysis, machine translation, etc. to help optimize models for better understanding and processing of natural language.

2. Application expansion in IoT: With the increasing number of IoT devices, how to manage and schedule these devices efficiently becomes a key issue. The population intelligence optimization algorithm can be used for resource allocation, task scheduling and network routing of IoT devices. By intelligently allocating computing resources, power resources, etc., it improves the operational efficiency and energy utilization of the devices; reasonably schedules tasks to ensure that they can be completed on time; and optimizes the network routing to reduce the delay and energy consumption of data transmission. In the smart home system, the use of group intelligence optimization algorithms can realize the energy management and cooperative work of smart home appliances, and improve the efficiency of home energy utilization and the convenience of life.

3. Potential applications in the field of blockchain: blockchain technology has been widely used in finance, supply chain management and other fields due to its features such as decentralization, tampering and high security. The population intelligence optimization algorithm can be combined with blockchain technology to solve some key problems in

blockchain. For example, in the consensus algorithm, the group intelligence optimization algorithm is used to optimize the selection of nodes and the voting mechanism to improve the efficiency and security of the consensus reached; in the optimization of smart contracts, the group intelligence optimization algorithm is used to find the optimal contract parameters and execution strategy to reduce the risk and cost of contract execution. In supply chain finance, applying the group intelligence optimization algorithm to the blockchain supply chain management system can realize more efficient supply chain financing and risk management.

7.3. In-depth and Improvement of Theoretical Research

1. Deepening of the theoretical foundation: further in-depth study of the theoretical foundation of the group intelligence optimization algorithm, revealing its intrinsic operation mechanism and law. For example, through mathematical modeling and theoretical analysis, in-depth study of the way of information interaction and collaboration between individuals in the algorithm, and how these interactions and collaborations affect the performance of the algorithm. Use mathematical tools such as probability theory, statistics and dynamics to build more accurate algorithmic models and analyze the theoretical properties of algorithms such as convergence, stability and robustness. Study the changing law of algorithm's performance under different problem sizes and complexities to provide more solid theoretical support for the application of algorithms[36] .

2. Enhancement of convergence analysis: convergence is one of the important indexes to measure the performance of population intelligence optimization algorithms. In the future, it is necessary to strengthen the analysis of the convergence of the algorithm and propose more effective convergence proof methods and convergence speed estimation methods. By improving the structure and parameter settings of the algorithm, the convergence speed and convergence accuracy of the algorithm can be improved. Study the convergence of the algorithm under different initial conditions and parameter settings, and provide guidance for the parameter tuning of the algorithm. Develop new convergence analysis tools and techniques to study in depth the convergence characteristics of algorithms under complex problems and large-scale data[37] .

3. Improvement of performance evaluation: establish a more scientific and comprehensive performance evaluation system to accurately assess the performance of the population intelligence optimization algorithm. In addition to the traditional indicators such as convergence speed and solution quality, factors such as the computational complexity, scalability, stability and interpretability of the algorithm should also be considered. The development of new performance evaluation indexes and methods can more objectively reflect the performance of algorithms in different application scenarios. Through a large number of experiments and practical applications, the performance of different algorithms is compared and analyzed to provide reference for users to choose the appropriate algorithm[38] .

8. Summary and Outlook

8.1. Importance of population intelligence optimization algorithms

As an emerging intelligent computing technology, population intelligence optimization algorithm shows unique advantages and strong vitality in solving complex optimization problems. It provides innovative solutions for many fields by simulating the collaborative behavior of biological groups in nature, and promotes the technological progress and development in various fields[39] .

In industrial production, the population intelligence optimization algorithm can optimize production scheduling, resource allocation and production processes, improve production efficiency, reduce production costs and enhance the competitiveness of enterprises. In the field

ISSN: 1813-4890

of transportation, it can optimize traffic route planning, logistics distribution and intelligent traffic management, alleviate traffic congestion, improve transportation efficiency and reduce energy consumption. In the field of energy, the population intelligence optimization algorithm helps to optimize the operation of energy systems, power dispatching and new energy generation prediction, improve the efficiency of energy utilization, and promote the sustainable development of energy. In addition, in the fields of image processing, data mining, bioinformatics, financial forecasting, etc., population intelligence optimization algorithms also play an important role, providing new ideas and methods for solving complex problems[40] .

The development of population intelligence optimization algorithms not only enriches the theory and methods of intelligent computing, but also provides a powerful tool for interdisciplinary research. It promotes the cross-fertilization of computer science, mathematics, biology, physics and other disciplines, and promotes the development of related disciplines. At the same time, the application of population intelligence optimization algorithms also brings great benefits to the development of social economy and improves people's quality of life[41] .

8.2. Expectations and Prospects for Future Development

Looking ahead, the population intelligence optimization algorithm is expected to make greater breakthroughs in theoretical research and practical applications. In terms of theoretical research, with the in-depth understanding of the behavior of biological groups and the continuous development of mathematical theory, the theoretical foundation of the group intelligence optimization algorithm will be more perfect. Researchers will further reveal the theoretical properties of the algorithm, such as convergence, stability and robustness, to provide more solid theoretical support for the optimization and application of the algorithm. At the same time, new population intelligence optimization algorithms and improvement strategies will continue to emerge to improve the performance and adaptability of the algorithms.

In terms of practical applications, the population intelligence optimization algorithm will be deeply integrated with emerging technologies, such as artificial intelligence, Internet of Things, blockchain, etc., to expand its application areas. In the field of artificial intelligence, it will provide more efficient optimization methods for machine learning, computer vision, natural language processing, etc., and promote the development of artificial intelligence technology. In IoT, population intelligence optimization algorithms will be used to optimize resource allocation, task scheduling and network routing of IoT devices, improving the operational efficiency and reliability of IoT. In the field of blockchain, it is expected to solve key problems such as consensus algorithm and smart contract optimization in blockchain, and promote the wide application of blockchain technology.

Population intelligence optimization algorithms will also play an important role in solving global problems, such as environmental protection, energy crisis and climate change. By optimizing solutions for resource allocation, energy use and environmental management, they will provide technical support for achieving the goal of sustainable development. With the continuous progress of technology and the continuous expansion of applications, the population intelligence optimization algorithm will play an increasingly important role in the future development of science and technology and social progress[42] .

Acknowledgements

This work is supported by Scientific Research Program of Chongqing College of International Business and Economics (Natural Science Programs). (KYZK2024012).

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