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Analysis of Efficient Optimization Algorithm for Information Nodes in Wireless Network Communication Chaos

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Abstract

Due to the poor node optimization effect of traditional mathematical model methods, an efficient node optimization algorithm based on ant colony genetic algorithm is proposed. The ant colony algorithm is a kind of bionic optimization algorithm, and its dynamics and self-similarity are very similar to the optimization principles of messy information nodes. "Chaos node efficient optimization algorithm" is dedicated to effectively aggregating various resources such as computing, storage, knowledge, communication, information, distributed around the world, serving the public, and realizing resource sharing and collaborative work. Among them, chaos nodes efficiently search for excellent problems. If the number of parent nodes and the order of the nodes are known, the ant colony genetic algorithm is used to find the largest supporting tree, so as to obtain the best node to obtain the largest number of iterations, thereby effectively optimizing the information node.

Keywords: Wireless Network Communication; Chaotic Nodes; Nodes; Efficient Optimization;

1. Introduction

Wireless network communication chaos refers to the complex and dynamic nature of wireless networks, which can lead to unpredictable behavior and performance issues. There are several factors that can contribute to wireless network communication chaos, including: Interference: Wireless networks operate on shared spectrum, and interference from other devices and networks can disrupt communication and lead to chaos. Mobility: The movement of devices and users in a wireless network can lead to changes in network topology and cause communication disruptions. Congestion: High levels of network traffic can cause congestion and lead to delays, packet loss, and other performance issues. Security: Wireless networks are vulnerable to various types of security attacks, such as denial-of-service (DoS) attacks, which can cause chaos in the network. Configuration: Incorrect or outdated network configurations can also cause chaos by leading to performance issues or security vulnerabilities. Managing the chaos of wireless network communication is a challenging task that requires the use of optimization algorithms and other techniques to improve network performance and stability. By analyzing and understanding the underlying causes of wireless network communication chaos, network administrators and engineers can develop effective strategies for managing and optimizing these complex systems.

Because the wireless communication network technology is mature, the signal is clear and stable, and it is easy to install and use, it is widely used in various professional fields. However, due to various reasons, many signals tend to interfere with practical applications [1]. If the processing is unsuccessful, the signal-to-noise ratio of the receiver will decrease, the communication quality will decrease, and the communication will not proceed normally. The efficient optimization algorithm using the "chaotic information" node must be able to make full use of this huge design space to obtain an approximate global optimization or global optimal layout [2-3].

Wireless networks have become an integral part of our daily lives and the efficient management of information nodes in these networks is critical for ensuring their performance. In this analysis, we will delve into the intricacies of various optimization algorithms and their impact on managing the chaos of information transmission in wireless network communication. We will evaluate the pros and cons of each algorithm and propose a solution that strikes a balance between efficiency and stability. This analysis will provide useful insights for network administrators and engineers looking to optimize their wireless communication systems.

Optimization algorithms play a crucial role in ensuring the efficient and effective functioning of various systems. In this analysis, we will focus on the optimization of information nodes in wireless network communication systems. We will explore the different algorithms available for this purpose and evaluate their effectiveness in managing the chaos of information transmission in these networks. The goal of this analysis is to propose a solution that balances efficiency and stability in the network, providing valuable insights for network administrators and engineers looking to optimize their wireless communication systems.

2. Literature Review

In recent years, there has been a significant amount of research on node optimization algorithms for wireless network communication [3]. One popular approach is the use of genetic algorithms (GA) for node optimization. GA has been found to be effective in optimizing node placement and routing in wireless networks [4-7]. It has been used to optimize network parameters such as energy consumption, throughput, and delay. Another approach is the use of particle swarm optimization (PSO) for node optimization. PSO has been used to optimize node placement, routing, and power allocation in wireless networks. It has been found to be effective in solving non-linear optimization problems and has a good convergence rate. Ant colony optimization (ACO) is another algorithm that has been applied to wireless network node optimization [8]. ACO has been used to optimize node placement, routing, and power allocation in wireless networks. It has been found to be effective in solving complex optimization problems and has been shown to be a useful tool for managing the chaos of wireless network communication [9]. Artificial bee colony (ABC) is another population-based algorithm that has been applied to wireless network node optimization [10]. ABC has been used to optimize node placement, routing and power allocation in wireless networks. It has been found to be effective in solving complex optimization problems, and it has a fast convergence and high-quality solutions.

Artificial neural network (ANN) is also a popular approach for wireless network node optimization. ANN has been used for node placement, routing and power allocation in wireless networks [11]. It can be used to optimize wireless network communication problems by learning from historical data and making predictions based on new input. Overall, there are many different optimization algorithms that have been applied to wireless network node optimization, and each has its own strengths and weaknesses. The choice of algorithm will depend on the specific characteristics of the problem and the desired outcome [12].

2.1. Genetic algorithm ant colony

Ant colony optimization (ACO) is an optimization algorithm that is based on the behavior and communication patterns of ant colonies. The algorithm simulates the process of ants searching for food by collectively finding the shortest path to a food source [13]. The ants communicate with each other by leaving chemical trails, called pheromones, that help guide other ants to the food source. Over time, the pheromone trails become stronger and the ants are able to find the food source more efficiently.

In the context of wireless network node optimization, ACO can be used to find the optimal placement and routing of nodes in a network [14]. The algorithm simulates the process of ants searching for the best path through a network by adjusting the strength of the pheromone trails based on the quality of the path. Over time, the ants converge on the best path, which corresponds to the optimal placement and routing of nodes in the network.

ACO has been found to be effective in solving complex optimization problems and has been shown to be a useful tool for managing the chaos of wireless network communication [15]. It has been used to optimize node placement, routing, and power allocation in wireless networks. It has a good convergence rate, and it has been found to be efficient in terms of computation time. However, the algorithm can be sensitive to the initial solution and the parameters that are used. Therefore, it is important to carefully tune these parameters to achieve the best results.

The Ant Colony Optimization (ACO) algorithm is a metaheuristic optimization technique that is inspired by the foraging behavior of ants. The algorithm simulates the process of ants searching for food by collectively finding the shortest path to a food source [15]. The ants communicate with each other by leaving chemical trails, called pheromones, that help guide other ants to the food source. The basic principle of the ACO algorithm is to maintain a set of ants that move in the search space and construct solutions by following the pheromone trails [17]. The ants construct solutions by moving from one node to another based on the pheromone trail and a heuristic function that represents the problem-specific information. The quality of the solutions is evaluated using an objective function and

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the best solutions are used to update the pheromone trails. In the context of wireless network node optimization, the ACO algorithm can be used to find the optimal placement and routing of nodes in a network [18]. The ants in the algorithm move through the network, leaving pheromone trails that represent the quality of the path. The algorithm adjusts the strength of the pheromone trails based on the quality of the path, and over time, the ants converge on the best path, which corresponds to the optimal placement and routing of nodes in the network. The ACO algorithm has a number of advantages over other optimization techniques, such as its ability to handle problems with a large number of variables and its ability to find global solutions [19]. However, it is sensitive to the choice of parameters and the initial solution, and it can be computationally expensive. Therefore, it is important to carefully tune the parameters and choose an appropriate initial solution to achieve the best results [20]. The ACO algorithm has been applied to a wide range of problems in wireless network optimization, including node placement, routing, and power allocation. It has been found to be effective in solving complex optimization problems and has been shown to be a useful tool for managing the chaos of wireless network communication.

The main calculations involved in the ACO algorithm are related to the updating of pheromone trails and the selection of the next node to visit. The pheromone trail update is an important step in the ACO algorithm, as it determines the strength of the trail and the probability of an ant choosing a specific path. The pheromone trail update is typically done using the following equation:

$$\Delta\tau(i,j) = (1 - \rho) * \tau(i,j) + \rho * \Delta\tau 0(i,j) \quad (1)$$

Where $\tau(i,j)$ is the pheromone trail on edge (i,j), ρ is the evaporation rate, and $\Delta\tau 0(i,j)$ is the pheromone trail update. The evaporation rate is a parameter that determines how quickly the pheromone trail evaporates and should be set to a value between 0 and 1. The pheromone trail update is calculated as the product of the quality of the path, represented by the objective function, and a constant value.

The selection of the next node to visit is also an important step in the ACO algorithm, and is typically done using the following equation:

$$P(i,j) = (\tau(i,j)\hat{}\alpha) * (\eta(i,j)\hat{}\beta) \,/\, \Sigma(k \in S)\, (\tau(i,k)\hat{}\alpha) * (\eta(i,k)\hat{}\beta) \quad (2)$$

Where $P(i,j)$ is the probability of an ant choosing edge (i,j), $\tau(i,j)$ is the pheromone trail on edge (i,j), $\eta(i,j)$ is the heuristic value of edge (i,j), α and β are parameters that control the relative importance of the pheromone trail and the heuristic value, and S is the set of edges that are available to the ant. The parameter α represents the pheromone importance and β represents the heuristic importance.

There are different variations of Ant colony algorithms, like Ant-System, Elitist Ant System (EAS), Rank-based Ant System (ASRank) and many others. Each one of them may have different calculation methods for pheromone update and path selection, but the basic concept remains the same. It is important to note that the ACO algorithm is a probabilistic and stochastic algorithm, so the optimal solution is not guaranteed and the results can vary depending on the initial solution and the parameter values. Therefore, it is important to run the algorithm multiple times with different parameter values and initial solutions to ensure that the best solution is found.

3. Research Method

3.1. Node optimization algorithm based on genetic algorithm ant colony

The energy of the information node determines the survival time of the wireless network. The routing protocol can save the survival time of the wireless sensor node and prolong the survival time of the sensor network.

3.2. Algorithm based on ant colony logic structure

Ant colonies can perceive environmental changes through pheromones, and communicate and cooperate with other ant individuals through pheromones. The behavior of ant colonies is random and independent, but they can complete the process from chaos to order without being affected by the external environment [4-6]. By expressing the combinatorial optimization problem in a standardized form, a decision-making mechanism is established and corresponding decision points are set. Individual ants use the concentration of pheromone to perceive changes in the environment. While exploring the future, they use the results of past behaviors. On the one hand, the distributed search feature of ant colony algorithms can be used to avoid falling into the local optimal situation [7]. In the initial state, the ants are randomly distributed on the grid computing nodes [8-9]. Calculate the state transition probability P of the k ant in resource i at time t according to the state transition formula.

$$P_{ij}^{k}(t)=\begin{cases}\frac{[\tau_{ij}(t)]^{\alpha}[\mu_{ij}]^{\beta}}{\Sigma_{\in U}[\tau_{iu}(t)]^{\alpha}[\mu_{iu}(t)]^{\beta}} & j,u \in \text{Online resources U} \\ 0 & \end{cases} \tag{3}$$

3.3. Mathematical model based on genetic algorithm

The idea of the basic ant colony algorithm is derived from the group behavior of real ants when foraging in nature, but the artificial ants in the basic ant colony algorithm have certain characteristics that real ants do not have[8]. For example, artificial ants have the ability to remember their past behaviors. The artificial ant has an algorithmic prohibition table called tabu, which stores the path that the ant has walked, so as to avoid the ant from taking the path that the ant has walked before [9- 11].TSP (traveling salesman problem) is a traveling salesman problem, which shows all aspects of combinatorial optimization problems, and has become a standard for testing the quality of new algorithms [12].

3.4. Features based on ant colony algorithm

This algorithm not only has the characteristics of positive feedback, but also implies a negative feedback mechanism, which makes ants more likely to choose a path with a higher pheromone concentration, and at the same time reduces the search range, and finally promotes the problem to develop in the optimal direction.. The implicit negative feedback mechanism of the algorithm makes it have a certain degree of randomness and keeps its search range in an appropriate range, which is conducive to global optimization [13-14]. In other words, the basic ant colony algorithm is to find a balance between the two in order to find the approximate optimal solution of the problem.

3.5. Search strategy based on chaotic thought

The basic principle of this method is as follows: According to some rules, the variable to be solved corresponds to a chaotic variable space, which uses ergodicity, randomness, regularity and other chaotic properties for optimization, and finally maps the solution to the optimization space. The global nature of chaotic search can improve the optimization performance of the ACO algorithm. Use the pseudo-randomness and lateral attributes of chaotic variables to optimize the search [15]. This effectively overcomes blind random search and provides excellent global search results.

3.6. Update strategy based on PSO pheromone

Inspired by the research on the problem of information transmission in the foraging process of birds, Kennedy and Eberhart proposed a new global optimization algorithm. The PSO algorithm has a global optimal position Xgbestand a unique local optimal position, so the PSO algorithm can be combined with the ACO algorithm for overall optimization. By using PSO's best Xp best solution and full population Xg best solution as reference points, and using other pheromones to update the route, each generation of ants can track these two best solutions and locate the ants so that they can be optimized.

3.7. Column-based search strategy

As a search strategy used in the stage of the efficient optimization algorithm for chaotic information nodes, the column search algorithm is a heuristic graph search algorithm used to search for the best expansion node in a limited set of graphs or trees, and is often used in systems with large solution spaces. The search tree of the pillar search algorithm in the system is constructed using a breadth-first strategy. Sort according to the nodes on each level of the tree, keep the number of nodes consistent with the width of the column, and delete the remaining nodes. Continue to expand these nodes to the next level and delete invalid nodes.

4. Algorithm performance simulation experiment analysis

Through the above process, an effective optimization algorithm for information nodes in wireless network communication is designed. However, it is not clear whether this algorithm can solve the problems of traditional algorithms. For this reason, a simulation comparison experiment is designed to test and analyze the performance of the algorithm. Through the experiment of 50-node wireless sensor network, the effectiveness of ant colony genetic algorithm simulation for effective node optimization technology is confirmed.

4.1. Comparative analysis of algorithm fitness

Through comparative analysis of the fitness of traditional mathematical modeling methods and node based ant colony genetic algorithms, the correctness of the method for node optimization is verified, and the result is shown in Figure 1.

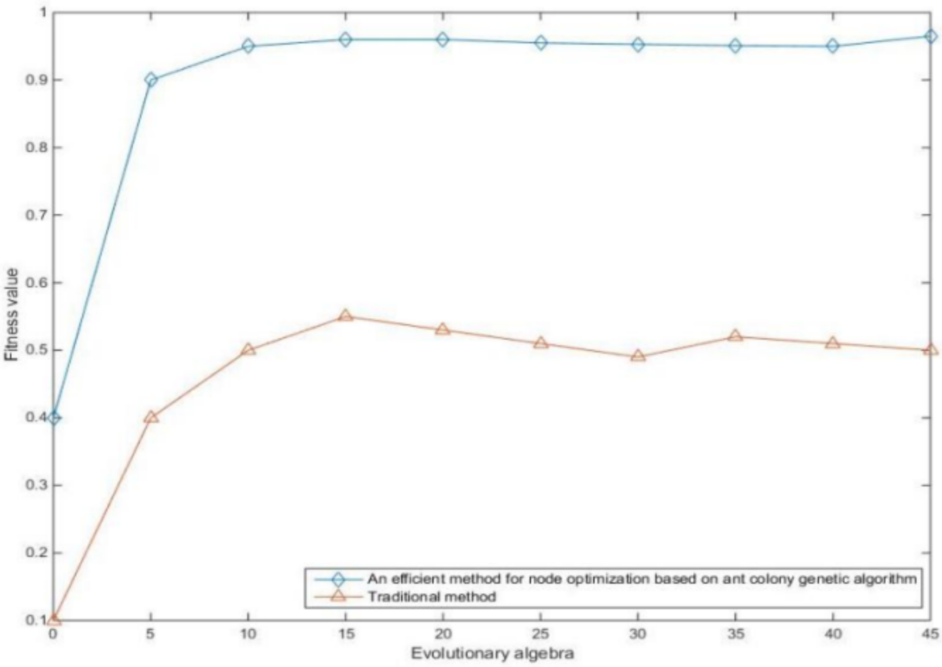

Figure. 1. Comparison of fitness values of the two methods

It can be seen from Figure 1 that this method has a higher adaptability than the traditional ant colony genetic algorithm, indicating that in the wireless sensor network, the energy consumption of the search node is the lowest, and the total energy of the network is in a balanced state.

4.2. Comparative analysis of optimization accuracy

In the experiment, the comparison of the optimization accuracy is obtained, as shown in Table 2. The optimization accuracy of this algorithm is much higher than that of the traditional algorithm, and the maximum value can reach 93%.

Table. 1. Comparison of optimization accuracy

Number of experiments	Proposed algorithm	Traditional algorithm
20	88%	44%
40	92%	61%

60	78%	54%
80	82%	58%
100	93%	66%

5. Conclusion

The efficient search algorithm for chaotic information nodes in wireless networks can significantly improve search accuracy and algorithm adaptability, and improve the problem of poor search results of traditional search methods. The simulation experiment results show that the algorithm can reach 90% of the optimal efficiency. This not only reduces the computing time of wireless sensor network nodes, but also reduces power consumption and effectively extends the service life of the sensors, providing advanced technical support for the application of wireless mobile networks. However, there is still room for improvement in the accuracy and adaptability of algorithm optimization, and further optimization of the algorithm is needed.

In conclusion, wireless network communication chaos is a complex and dynamic problem that can lead to unpredictable behavior and performance issues. There are several factors that can contribute to wireless network communication chaos, including interference, mobility, congestion, security, and configuration. To manage and optimize these complex systems, various optimization algorithms have been proposed and applied to wireless network node optimization. These include genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC) and Artificial Neural Network (ANN). Each algorithm has its own set of strengths and weaknesses, and the choice of algorithm will depend on the specific characteristics of the problem and the desired outcome. Overall, it is important to analyze and understand the underlying causes of wireless network communication chaos to develop effective strategies for managing and optimizing these systems

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