Application of Multi-Objective Optimization Problem Based on Genetic Algorithm

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Abstract. With the rise and rapid development of mobile communications, smart terminals and data mining technologies, we are entering the mobile Internet era. When dealing with the multi-objective problem encountered in the network, it cannot control the operation strategy of various specific applications by itself. Therefore, a fault-tolerant mechanism is needed to provide a high degree of flexibility at the application level. When the mobile database changes, only the error handling strategy needs to be modified without considering the specific code of the application. This paper mainly introduces the application research of multi-objective optimization problem based on genetic algorithm. In this paper, the application research of multi-objective optimization problems based on genetic algorithm is used, and the multi-objective evolutionary algorithm still needs to be improved in terms of convergence and distribution. Some algorithms with better convergence performance often have slightly insufficient distribution performance, but the distribution performance is relatively low. The best algorithm often needs to improve its convergence performance. Therefore, it is of great significance to study the multi-objective co-evolution genetic algorithm. The experimental results of this paper show that the application research for the multi-objective optimization problem based on genetic algorithm increases the optimization rate of multi-objective problem by 14%, and the limitation of the multi-objective optimization problem of genetic algorithm provides good indoor path planning for the application of genetic algorithm. Analysis, discussion and summary of the methods and approaches to enrich the academic research results.

Keywords: Genetic Algorithm, Scheduling Algorithm, Mobile Database, Multi-Objective Optimization

1. Introduction
In the research of internal environmental information service, the algorithm first adopts the mechanism of multi-group co-evolution, and first makes each group evolve independently, when each group reaches a state of evolutionary stagnation [1-2]. Select representative individuals from each population to form a representative individual set, secondary search area and peripheral search area. The key search area is the most likely to find the optimal solution, so the search granularity in this area is the largest, while the other two search areas. The search granularity is reduced step by step, thus
effectively improving the efficiency of algorithm optimization [3-4]. There are many applications and requirements under mobile databases. Specific applications have different tolerances for errors. Therefore, the error detection service of the grid fault tolerance mechanism must be able to meet the different requirements of different applications and requirements for error detection functions, and can be realized according to the user's requirements. Specific needs to develop corresponding error detection services [5-6].

With the advancement of science and technology and the rapid development of the Internet, the design of multi-objective optimization problems in complex environments is enhanced. Bhattacharyya B divides the static scheduling algorithms into table scheduling algorithms, clustering algorithms, task replication algorithms, In a few special cases, such as directed random search algorithm, a scheduling algorithm with polynomial time complexity can be obtained [7]. The system formed by various resources connected by Scott JK through the Internet is a typical heterogeneous system, and the resources possessed by this system are incomparable to any other system. Whether it is a homogeneous system or a heterogeneous system, one of the key issues to obtain high performance is task scheduling [8]. For a tree graph with the same node weights, an algorithm with linear time complexity is proposed, which is based on task replication-based scheduling algorithms for isomorphic systems [9-10]. However, there are errors in their experimental process, which leads to inaccurate results.

The innovation of this paper lies in the application research of multi-objective optimization problems based on genetic algorithm. Research on the application of genetic algorithm-based multi-objective optimization problems, and analyze the effective countermeasures of scheduling algorithms. The performance of the task scheduling algorithm in the grid needs to be tested in various environments. The establishment of a real mobile database requires different resources, which is time-consuming, labor-intensive and expensive. Due to the dynamics and differences of grid resources Due to the structural nature, the experiments of task scheduling algorithm performance testing are often not repeatable and controllable. The aim is to find a new path suitable for the current multi-objective optimization development through this research.

2. Scheduling Algorithm under Genetic Algorithm

2.1. Genetic Algorithm

The genetic algorithm has two stages: task priority calculation and processor selection. In the task priority calculation phase, the scheduling algorithm takes the task's up-order value as the task's priority value, and arranges the tasks in the descending order of the up-order value to form a task scheduling sequence. If the task's up-order value is the same, the task is randomly selected. In the processor selection stage, the scheduling algorithm selects tasks from the task scheduling sequence in turn: Under the premise of satisfying the priority constraint relationship between tasks, the insertion strategy is used to allocate the task to the earliest idle gap of the processor, so that the task can be completed to the minimum. The processor idle gap in this paper refers to the two tasks that are successively allocated to the same processor. In the first stage, the scheduling algorithm uses the average running cost and the average communication cost to calculate the upward and downward ranking values of all tasks. The sum of the upward sorting value and the downward sorting value is used as the priority value of the task.

The scheduling algorithm first determines the critical path task before determining the task sequence. The scheduling algorithm first marks the starting task as a critical path task, and then selects the task with the highest priority value from its immediate successor tasks to mark the critical path task, and repeats the critical path task mark Operation until the end of the task has been marked, then the critical path task is determined. If there is more than one task with the highest priority in the immediate successor task, the first one (the one with the smallest task number) is selected and marked. When determining the task scheduling sequence, the scheduling algorithm follows the determined critical path task sequence. If the critical path task is already a ready task, the critical path task enters
the task scheduling sequence first, otherwise the task with the highest priority value is selected from other ready tasks. Enter the task scheduling sequence, repeat the task enqueue operation until the end task has entered the task scheduling sequence, then the task scheduling sequence is determined. The ready task here refers to the task whose direct predecessor tasks have all entered the task scheduling sequence, and the start task is the first ready task. Appropriate application of this function can design an effective algorithm in the multi-objective optimization plan, which has the following form.

\[
\begin{align*}
I_{A1} &= U_{A1} \sigma C_{01} \\
I_{B1} &= 0 \\
I_{C1} &= U_{C1} \sigma C_{01} \\
\end{align*}
\]

The calculated value of the algorithm is as follows;

\[
d\mathcal{N}_t = -\mu * F
\]

The test shall use the following formula:

\[
X_t = \sum_{j=0}^{q} \theta_i e_{i-j}
\]

2.2. Multi-Objective Problem Analysis

A staged multi-objective co-evolutionary algorithm. Current multi-objective evolutionary algorithms with better convergence performance tend to have slightly insufficient distribution performance, while multi-objective evolutionary algorithms with better distribution performance tend to have weaker convergence performance. Therefore, multi-objective evolutionary algorithms need to further improve convergence performance and distribution performance. The staged multi-objective co-evolutionary algorithm is divided into two evolution stages. The population evolution stage focuses on improving the convergence performance of the algorithm, and the outstanding individual re-evolution stage focuses on improving the distribution performance of the algorithm, thereby simultaneously improving the convergence performance and distribution performance of the algorithm. In the stage of population evolution, learn from the ideas of cultural algorithms, and at the same time, various groups learn the culture of excellent populations during the evolution process, and swallow disadvantaged populations; in the re-evolution stage of excellent individuals, individuals in the belief space of various groups converge to the total belief. The space is further evolved in the way of mutation within the neighborhood, exploring better individuals near excellent individuals, and improving the uniformity of population distribution. The simulation experiment test shows that, compared with NSGA II, the algorithm not only improves the convergence performance, but also improves the distribution performance through staged evolution.

3. Genetic Algorithm Mobile Database Analysis

3.1. Scheduling Multi-Objective Optimization Problems

It has also been applied in the research of scheduling problems, but the conventional genetic algorithm is prone to premature maturity and late evolution stagnation. The reason is that the selection pressure in the early stage of evolution leads to the loss of the effective alleles of the individual, which makes the individuals within the population quickly converge in the pattern, trapped in the local optimal point and appear premature: in the later stage of evolution, the pattern of the individuals within the population converges more obviously. It is difficult to produce new individuals and obtain new best points, and there is a phenomenon of stagnant evolution. Many scholars have explored ways to solve
this problem from different angles. Select tasks in the task scheduling sequence for assignment. When assigning a task, follow the following three steps. Select the processor with the smallest start time for the current task. Check the idle time gap size in the processor selected in the previous step in order to copy the selected key parent tasks. If copying the selected key parent task can reduce the start time of the current task, confirm that the copy scheduling algorithm only selects the key parent task that needs to be copied in the first two key parent tasks. Compared with other task copy algorithms, its algorithm time The complexity is small, close to the non-task copy algorithm. There are many idle time gaps in the processor in the scheduling scheme: the scheduling algorithm adopts the task replication strategy, and the utilization rate of the processor is much higher.

3.2. Mobile Database System
The scheduling algorithm is designed with fitness function, crossover probability function and mutation probability function that are automatically adjusted as evolution progresses. Different selection pressures, crossover pressures and mutation pressures are used in different stages of evolution to better improve the phenomenon of premature convergence and later stages. A new form of co-evolution genetic algorithm is proposed to obtain an automatically adjusted scheduling strategy. The algorithm requires a suitable dispatch rule to be assigned to each processor, which matches and adapts to the rules used by adjacent processors. The algorithm introduces the concept of derived contribution feedback. This algorithm can effectively suppress premature convergence, and produce better space adaptive allocation rules than other algorithms. Generally speaking, genetic operations are composed of selection, crossover, and mutation operators. These operators are based on key parameters such as fitness, crossover probability, and mutation probability. The quality of the genetic algorithm's solution depends heavily on these parameters. Suitability directly affects the scheduling performance of the algorithm. The specific results are shown in Table 1.

Table 1. Comparison of several wireless data transmission methods

| Skill                        | Number of people | Skill                      | Number of people |
|------------------------------|------------------|----------------------------|------------------|
| Operational standardization  | 30               | Shorten experiment time     | 13               |
| Add fun                      | 12               | Fully understand the principle | 9               |
| Expand the amount of knowledge | 29             | Improve learning efficiency | 15               |
| other                        | 8                |                            |                  |

4. Mobile Database Analysis under Scheduling Algorithm

4.1. Mobile Environment Model
The laboratory project of this paper proposes a multi-objective optimization problem algorithm based on genetic algorithm, to study the feasibility and performance of task scheduling algorithm, and make corresponding improvements. The real grid can be abstracted into four entities; users, applications, Middleware, resources, these four entities constitute the main components of the mobile database. Grid simulation simulates the mobile database based on these four components. The simulation of users is to realize the access to grid resources and the submission of grid jobs by simulating the access characteristics of users. The simulation support for user access characteristics can be closer to the simulation of the real mobile database. The simulation of the grid application by the grid simulator is simulated by the authenticity and type of the grid application. The applications used by the grid simulator are divided into real and virtual: the simulation results obtained by the real application are relatively closer to the real, while the virtual application is more suitable for simulation experiments.
In the simulation experiment, all simulated resources are used. These resources can be divided into two types: computational and data types. The simulation of grid resources is the basis for grid simulation. The specific results are shown in Figure 1. The abscissa is the number of synchronizations \( Y \), and the ordinate is the absolute value of the error. The test results show that the increase in the number of synchronization makes the error decrease exponentially.

![Figure 1. Mental model work](image)

**4.2 Multi-Objective Optimization Problems**

Optimized for multi-objective problems. According to different criteria, the scheduling algorithm can be divided into different types. According to whether the subtasks of the task system are deterministic or uncertain, static scheduling is sometimes called offline (of-line) scheduling. Dynamic scheduling refers to the scheduling of dynamic task systems. Before the task system runs, the number of subtasks, task running costs, communication and synchronization requirements, and data dependencies are uncertain, and will change dynamically as the task system runs. Dynamic scheduling is particularly suitable for the scheduling of real-time tasks. For dynamic scheduling, the scheduler will continue to run with the change of the task system state, and its operating overhead is not negligible, and it is an important factor affecting the efficiency of the task system. Most of the existing scheduling algorithms are static scheduling algorithms, and several algorithms proposed in this paper also belong to static scheduling algorithms. For static scheduling algorithms, the static scheduling algorithm is divided into Independent tasks, Duplication according to the relationship between tasks, whether the task running cost is a unit, whether to consider the communication cost, whether to adopt the task replication strategy, the number of processors and the connection status, etc., UNC, BNP, APN, etc. to several categories. The specific results are shown in Table 2.

| Table 2. Statistical table of sample library |
|-----------------------------------------------|
| Normal                        |
| Number of Transformers | Independent tasks |
| Total Sample          | Duplication      |
| Training Samples       | UNC              |
| Validation Sample      | BNP              |

One is to improve and test on the basis of the actual system, and the other is to complete the experiment by separately compiling the corresponding prototype system. Mobile database is a technology with broad development and research prospects. Make it truly an open and universal test platform to provide a research foundation for our country's research in the field of mobile object databases. An adaptive genetic scheduling algorithm is proposed for multi-objective optimization to improve the phenomenon of premature convergence and late evolutionary stagnation. In terms of moving object indexing technology, it is necessary to study new indexing methods suitable for
different situations, especially the need to conduct in-depth research on R-tree-based moving object indexing. In terms of location-related query processing, research on query processing methods combining multiple technologies with application requirements as the subject. Such as combining mobile object database technology and spatial database technology to meet more complex query requirements: combining WEB data processing technology and location-related data processing technology to provide more personalized and intelligent services. The specific results are shown in Figure 2. When the number of attributes is the same, as the number of sample data increases, the efficiency of the mobile database has been significantly improved.

![Figure 2. Moving object index](image)

5. Conclusions

Although this paper has a lot of deficiencies in the application research of multi-objective optimization problems based on genetic algorithms. The academic value of mobile database research. Mobile data technology has a very high academic starting point and involves many disciplines. It uses and inherits traditional database technology in data storage, organization and management. The application of genetic algorithm to multi-objective optimization problems not only requires extensive theoretical knowledge, but also a solid theoretical foundation and ability. The application research of multi-objective optimization problem based on genetic algorithm still has a lot of in-depth content worthy of study. There are still many steps in the research of mobile database analysis because of space and personal ability, etc., which are not covered. In addition, the actual application effect of the related experiments of the scheduling algorithm can only be compared with the traditional model from the level of theory and simulation.

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