QoS routing algorithm for OBS networks based on a multi-objective genetic algorithm

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ABSTRACT To optimize the QoS of optical burst switching networks, a QoS routing optimization algorithm based on a multi-objective genetic algorithm is proposed. A Bayesian network model is used to locate the fault of optical burst switching network and obtain the fault location of the transmission link of optical burst switching network; In this position, the routing optimization algorithm based on a multi-objective genetic algorithm transforms the multi constrained network quality of service routing optimization problem into a constrained multi-objective routing optimization problem. Under multiple constraints, the best path of optical burst switching network service is obtained to realize the optical burst switching network quality of service routing optimization. The results show that after applying the proposed algorithm, the average delay of video, text and picture transmission in an optical burst switching network is less than 400ms. The proposed algorithm can improve the packet delivery rate of information transmission in an optical burst switching network, reduce the transmission delay, blocking probability and use cost of an optical burst switching network, and optimize the service quality of an optical burst switching network.

INDEX TERMS Bayesian network model; network failure; transmission link; routing optimization; multiple constraints; optimal path

I. INTRODUCTION

The 21st century is an information age with networks as the core. People's demand for information is increasing day by day. Some image information related to people's vision, such as videophone, digital image, HDTV and other broadband business markets is rapidly expanding [1]. All kinds of new business, such as distance education, teledicine, home shopping, home office are booming, which must rely on a complete network. The network has become the pulse of the information society, and it is changing all aspects of human social life [2-3]. At present, the optical fibre communication network has become the foundation of the high-speed Internet backbone network, and the development and maturity of wavelength division multiplexing (WDM) provide massive bandwidth, which makes all-optical switching possible. To meet the explosive growth of multimedia services represented by the Internet, a variety of new optical communication technologies have been proposed and studied, and have achieved rapid development.

There are three kinds of WDM-based optical switching technologies, namely optical circuit switching (OCS), optical packet switching (OPS) and optical burst switching (OBS). Optical burst switching combines the advantages of optical path switching and optical packet switching and avoids their disadvantages. Moreover, based on the development status of optical devices and optical technology, OBS technology is easy to implement, and can flexibly support the burst services represented by P [4].

OBS network, as the basic technology of next-generation optical Internet, must provide differentiated services for various high-level services and provide good quality of service (QoS). Specifically, it must focus on the following issues: first, how to solve the problem of high loss rate caused by the competition between data bursts (DB); second, how to reduce the end-to-end delay (including the assembly process) of DB. Because the OBS network uses one-way wavelength channel resource reservation, and the core node has no or only limited capacity FDL buffer, the DB conflict in the network is inevitable. This makes the QoS problem in the OBS network more complex and difficult to deal with than that of an IP
network. Therefore, the research of QoS performance has become a hot issue in the OBS network. Literature [5] proposes a wireless sensor network quality of service (QoS) routing algorithm. According to an idealized wireless sensor network QoS evaluation index system, the uncertainty index in the wireless sensor network QoS evaluation is converted into a Vague value utilizing the Vague set method. The definition of the positive ideal object and the negative ideal object determines the distance between the object to be evaluated and the positive and negative ideal object, and uses the score function value to define the Vague value of the qualitative index, and then obtains the evaluation value of the object to be evaluated by the weighting method. According to this value, the wireless sensor network quality of service routing optimization is realized. Literature [6] proposed an adaptive routing algorithm that can meet multiple QoS requirements. First, a software-defined satellite network multi-constraint routing optimization model is established, and then the Lagrangian relaxation method is used to relax the model. Finally, the gradient method is used for an iterative solution to search for the optimal path that satisfies multiple QoS such as bandwidth, delay, and packet loss rate. However, the network transmission information packet delivery rate of the above two algorithms is low, the average delay of the transmission target node is longer, and the blocking probability and use cost are both high.

Given the problems of the above algorithms, this paper proposes a multi-objective genetic algorithm-based routing optimization algorithm for optical burst switching network quality of service, which generates a set of optimal non-inferior paths whose performance is balanced between different performance goals. And according to the nature of the business adaptively configure the path to optimize the service quality of the optical burst switching network. The specific research route of this paper is as follows:

(1) Bayesian network model is used to locate the fault of the optical burst switching network, and the fault location of transmission link of optical burst switching network is obtained;

(2) In the transmission link fault location of the optical burst switching network, the routing optimization algorithm based on a multi-objective genetic algorithm transforms the multi-constrained network quality of service routing optimization problem into a constrained multi-objective routing optimization problem;

(3) Under multiple constraints, the optimal path of optical burst switching network service is obtained to realize the QoS routing optimization of the optical burst switching network.

II. QOS ROUTING OPTIMIZATION ALGORITHM BASED ON MULTI-OBJECTIVE GENETIC ALGORITHM FOR OBS NETWORKS

A. Fault location algorithm for OBS network based on Bayesian network model

Optical burst switching network fault mainly takes the transmission-blocking of optical burst switching network as the core problem. Therefore, this paper uses the fault location algorithm of the optical burst switching network based on the Bayesian network model to accurately locate the transmission-blocking location of the optical burst switching network [5-7]. In this position, the implementation of targeted QoS routing optimization in the OBS network can greatly reduce the processing efficiency of QoS routing optimization in the OBS network.

Fault propagation model Fault propagation model

The probability-weighted bipartite graph model can simply and accurately express the relationship between link failure and symptom in the OBS network, which is mainly composed of three parts: the bipartite node set \( V \) composed of failure and symptom, \( V = F \cup S \), \( F \) is the link failure set of OBS network, \( S \) is the symptom set. The directed edge set \( E \), which expresses the fault points to symptom, \( E = F \times S \); the set \( P_{F \times S} = \{p\{s|f\}|f \in F, s \in S\} \) consists of all edge weights \( p\{s|f\} \), where \( p\{s|f\} \) refers to the probability value of the symptom \( s \) under the condition of fault \( f \). In the deterministic model, \( P_{F \times S} = \{0,1\} \); in the non-deterministic model, \( P_{F \times S} = (0,1) \).

FIGURE 1. Probability weighted bipartite graph

To better study, the probability-weighted bipartite graph, the parameters \( F(S_i) \), \( S(f_i) \) and \( S_o \) are defined. \( F(S_i) \) represents the set of all transmission link failures associated with symptoms \( S_i \); \( S(f_i) \) represents the set of all transmission link failures associated with symptoms \( f_i \); \( S_o \) represents the set of observable symptoms. Parameter definition

The explanation degree \( a \) of Bayesian symptoms is defined. The Bayesian symptom explanation degree not only reflects the difference of feedback information of a symptom to multiple related failures but also reflects the difference of information provided by multiple symptoms to the same related failure,
which more accurately expresses the possibility of transmission link failure [8-10]. The definition process of Bayesian symptom explanation degree \( a \) is divided into the following three steps:

1) OBTAINING BAYESIAN POSTERIOR PROBABILITY INFORMATION

Equation (1) is used to calculate the posterior probability \( p(f_i|S_i) \) in turn. \( p(f_i|S_i) \) is the probability of fault \( f_i \) under the condition of symptom \( S_i \). The larger the \( p(f_i|S_i) \) value is, the more likely the transmission link fault \( f_i \) is to explain the symptom \( S_i \).

\[
p(f_i|S_i) = \frac{p(f_i)p(S_i)}{\sum_{f_j \in F(S_i)} p(f_j)p(f_j|S_i)} (1)
\]

where \( p(f_j) \) is the probability of transmission link failure without symptoms.

2) NORMALIZATION OF BAYESIAN PROBABILITY INFORMATION

For different transmission link faults, \( f_i \in F(S_i) \) and \( p(f_i|S_i) \) values are different, so different \( f_i \in F(S_i) \) has a different explanation for symptom \( S_i \). After normalization calculation, the explanation degree \( a(f_i,S_i) \) of fault \( f_i \) to symptom \( S_i \) can not only ensure that symptom \( S_i \) can be explained by at least one fault in the transmission link fault set \( F(S_i) \) but also express the possibility of choosing fault \( f_i \) to explain the symptom \( S_i \). For each symptom \( S_i \), equation (2) is used to normalize the posterior probability. The explanation degree of symptom \( S_i \) for transmission link fault \( f_i \) is defined as \( a(f_i,S_i) \). From a statistical point of view, the value of \( a(f_i,S_i) \) can be interpreted as the number of symptoms \( S_i \) of transmission link failure \( f_i \).

\[
a(f_i,S_i) = \frac{p(f_i|S_i)}{\sum_{f_j \in F(S_i)} p(f_j|S_i)} (2)
\]

3) CALCULATION OF BAYESIAN SYMPTOM EXPLANATION DEGREE A OF TRANSMISSION LINK FAILURE

Equation (3) is used to calculate the Bayesian symptom explanation degree \( a(f,S_N) \) of possible fault \( f \) to the symptom set \( S_N \) one by one. The value \( a(f,S_N) \) indicates the number of symptoms in the symptom set \( S_N \) of transmission link fault \( f \). The larger the \( a(f,S_N) \) value is, the greater the possibility of transmission link failure is.

\[
a(f,S_N) = \sum_{f_j \in F(S_N)} p(f|S_N) (3)
\]

Steps of positioning algorithm

The main idea of the algorithm is to sort the possible faults according to the possibility of transmission link failure in an optical burst switching network, and then solve the sorted transmission link fault set by heuristic method, and find out the fault hypothesis set \( H \) which is most likely to explain the observed fault symptom set \( S_N \subset S_O \) of the transmission link. That is, the explanation \( a(f_i,S_i) \) of the related fault is obtained by processing the fault symptom of each transmission link in the optical burst switching network. The summation can obtain the explanation degree \( a(f_i,S_i) \) of each possible fault to symptom set \( S_i \). According to the size \( a(f_i,S_i) \), the possible faults are arranged, and the corresponding possible faults are taken out in sequence. The acquired symptom sets are explained.

The faults that can update the explanation symptom set are added to the transmission link fault hypothesis set \( H \) until all the symptoms are explained.

The Bayesian symptom explanation degree \( a(f,S_N) \) of each fault \( f \) in all transmission link fault sets \( F(S_N) \) associated with symptom \( S_N \) is obtained to form a set \( F \) and the elements \( F \) are sorted from large to small. When the most likely first \( m \) transmission link failures \( F \) completely cover all the observed symptom sets \( S_N \), it is considered that the optimal transmission link failure hypothesis set is found.

If Transmission link failures of multiple optical burst switching networks to be independent of each other cause a symptom, any transmission link failure can cause this symptom. Transmission link failure independently assumes that different transmission link failures are independent of each other[11].

The inputs are propagation model of transmission link fault in optical burst switching network; observable symptom set \( S_N \); symptom set \( S_N \subset S_m \) observed in a single time window; symptom observable rate \( OR(OR = S_m / S) \); symptom loss rate \( LR(s) \); symptom false rate \( SSR(s) \).

The output is the optimal fault hypothesis \( H \) which can explain \( S_N \). Each symptom \( S_N \) is explained by at least one transmission link fault in the optical burst switching network in \( H \), and the fault contained in \( H \) is the most possible to generate a symptom set \( S_N \).

To sum up, the positioning steps are as follows:

Step 1. Let \( H = \emptyset \);

Step 2. For each symptom \( s_j \), the possible fault sets of other burst switching network links are found to form the fault subset \( F(s_j) \) to be selected;

Step 3. For each fault \( f_j \) in \( F(s_j) \), \( a(f_j,S_j) \) is calculated and added to set \( F_j \);

Step 4. The initialization symptom set \( S_N \) is empty;

Step 5. The explanation degree of symptoms in the set \( F_j \) is sorted from high to low, and \( a \in F_j \) is taken out in turn, to execute until \( |S_N \setminus S_j|/|S_j| = 1 \);

Step 5.1 The corresponding \( f_j \) of \( a \) is obtained;

Step 5.2 The corresponding \( S_i \) of \( f_j \) is obtained;

Step 5.3 If \( S_j \cup S_i = S_m \), \( H = H \cup \{f_j \} \);

Step 6. The location set of transmission link fault in optical burst switching network is output.

B. A routing optimization algorithm based on a multi-objective genetic algorithm

Aiming at the location of transmission link fault in optical burst switching network in Section 2.1, a routing optimization algorithm algorithm based on a multi-objective genetic algorithm is used to obtain the best path of optical burst switching network service under multiple constraints, to realize the QoS routing optimization of the optical burst switching network.

Algorithm idea and model

Since only a complete end-to-end path is a solution in the QoS routing calculation of OBS networks, it is an important problem to generate feasible solutions from some solutions (including infeasible solutions) by iterative optimization [12-13]. Our idea is to first use the Dijkstra algorithm to generate a set of initial complete paths according to the changing weight combination, and generate new paths through the appropriate crossover and mutation operation in the genetic algorithm. The basis and
premise of individual evolution selection are to determine the appropriate QoS constraints and multi-objective model [14].

Usually, the routing algorithm takes the minimization of path cost or total delay as the indexes; these two indexes are also taken as two sub-objects, and other common parameters such as minimum bandwidth and packet loss rate as constraints. Because there are many kinds of constraint parameters, considering the simplicity of the model, do not list them one by one. The main idea is to take them as constraints of the optimization model[l5]. For optical burst switching network $G(N,E)$ and any path $P$, suppose there is a parameter quadruple $(Cost(i), Delay(i), Bandwidth(i), Loss(i))$ of link $i$, which indicates the cost, delay, available bandwidth and packet loss rate of the link respectively. $Bandwidth_i$ and $Loss_i$ are the minimum remaining bandwidth and maximum packet loss rate of the path required by the communication service respectively. Then a constrained multi-objective routing optimization model is formally described as follows:

$$\text{minimize } F(P) = \left[ \sum_{i \in P} Cost(i), \sum_{i \in P} Delay(i) \right]$$

In equation (4), the information transmission path $P$ of the OBS network is constrained by two restrictions

$$\text{Bandwidth}(P) = \min_{i \in P} \left[ \text{Bandwidth}(i) \right] \geq \text{Bandwidth}_i \quad (5)$$

$$\text{Loss}(P) = 1 - \prod_{i \in P} (1 - \text{Loss}(i)) \leq \text{Loss}_i \quad (6)$$

Where, $\text{Bandwidth}(P)$ and $\text{Loss}(P)$ are the minimum remaining bandwidth and the maximum packet loss rate of the path required by the communication service of the path $P$ in turn. Equation (4) means minimizing the vector so that all sub-targets in the target $F(P)$ are minimized at the same time.

The characteristics of multi-objective optimization lie in the incomensurability and conflict between objectives. Generally, there is no common minimum point among all objective functions[16-18]. Therefore, it is necessary to introduce the concept of a non-inferior solution, which is also known as a satisfactory solution or Pareto optimal solution. The result of multi-objective simultaneous optimization is to produce such a group of mutually balanced solutions, and the objective values of these solutions are not inferior to each other under the constraint conditions.

The traditional multi-objective optimization methods, such as the weighting method and constraint method, can provide certain solving abilities, but they are very sensitive to the shape of Pareto optimal front-end, and can not deal with the concave part of the front-end, or the heuristic knowledge related to application background can not be obtained. Genetic algorithms (GAs) have emerged in dealing with multi-objective problems. Its advantage is that it can deal with large-scale search space and produce multiple equilibrium solutions during a single round of optimization. Although GAs can find Pareto optimal solution or suboptimal solution in single round comparison because of its inherent parallel performance, the traditional genetic operation cannot be used to find a non-inferior solution set, which has special requirements and characteristics different from a single-objective evolutionary algorithm, especially in the processing of constraints.

Process description

Based on the above ideas and models, a multi-objective genetic algorithm (MGA) is designed for constrained multi-objective routing problems. The steps are as follows:

Step 1: Dijkstra algorithm is used to generate multiple paths from the source to the destination.

Because the Dijkstra algorithm can only produce one shortest path for a single metric of a path, the linear combination method is used to combine the cost and delay of each link in the OBS network, and the shortest path is found according to the aggregation of a single metric. At this time, the link $i$ weight becomes:

$$w(i) = \alpha \times \text{Cost}(i) + \beta \times \text{Delay}(i) (7)$$

Where, $\alpha$ and $\beta$ are multiplier factors between 0 and 1, and $\alpha + \beta = 1$. In this step, the path obtained by this method is not required to be within the limits of the minimum bandwidth and packet loss rate, that is, the generated path may exceed the constraints. Another problem is how to determine the appropriate coefficient under the premise of comprehensive cost and delay. The method of variable weight is proposed to randomly generate a random decimal $\alpha$ and get the corresponding $\beta$, and use the Dijkstra algorithm to generate multiple so-called shortest paths many times, as the initial population of genetic algorithm.

Step 2: a multi-objective genetic algorithm is used to search a group of multi-objective QoS optimal non-inferior paths that meet the constraints. The details are as follows:

1) The initial path generated in step 1 is mapped to an individual in the genetic space, the chromosome structure is composed of the sequence of all nodes on the path to form an initial population with the population size of $\rho$, and an empty auxiliary external population set $\rho'$ is generated. Usually $\rho > \rho'$.

2) The individuals with the optimal non-inferior solution and constraints within the specified range are copied to the external set.

3) If there is a bad solution in the external set, it will be deleted; if the number of individuals in the external set exceeds the specified number, the average association method will be used to implement clustering processing, so that it does not exceed the specified number [19].

4) The fitness values of individuals in the population are calculated.

5) The binary League rules are used to select the dominant individuals from the group to form a pairing pool, and the resulting dominant individuals $\text{gen}$ are mixed with the individuals in the external set and assigned to the next generation group.

6) Crossover and mutation operations are carried out on individuals in the group.

7) If $\text{gen}$ reaches the specified maximum cut-off generation number $G$, evolution will stop; otherwise, go to (2).

The advantage of using an external set is to keep the diversity of the population and to output the evolution result easily. The fitness of the individual in step (4) is $\text{Fitness} = n / \rho$ and $n$ is the number of individuals that are relatively better than the individual in the outer set. The fitness is minimized, and the minimum fitness value has a high replication probability. The relative superiority relations between two individuals with multi-objective constraints are classified into four categories. In the first category, if all the individuals satisfy the constraints, the one with the best goal is superior;
The second type: when the individuals are beyond the scope of constraints, the small amount of excess one is better; The third type: if the individual exceeds the same constraint range, the one with the best goal is superior; The fourth category: if the individuals exceed the same constraint range and the target values are not inferior to each other, both are excellent. In the measurement of the degree of violation of the constraint range, the usual method is to treat the constraints of different orders of magnitude equally, which inevitably leads to inaccurate results. The linear scaling of constraint values is proposed to use, so that the violation degree of each constraint value is in the same order of magnitude, and ensures that the constraint violation amount after scaling is greater than 0. According to the problem model in this paper, the constraint violation degree $\text{Const}(P)$ of a path $P$ is:

$$\text{Const}(P) = 100.0 \times \left( \frac{\text{Loss}(P) - \text{Loss}_{\text{min}}}{\text{Bandwidth}(P) - \text{Bandwidth}_{\text{min}}} \right)^{8}$$

The genetic operation of the information transmission path in the OBS network includes path crossover and path mutation, which are important means to generate other paths. Path crossing is a pair of paths that exchange each other's sub-paths, but when a pair of paths do not have a common cross node, they cannot achieve crossover operations. If the string is conventionally crossed by force, illegal paths may be generated. An example of path crossing is shown in Figure 2. The steps are as follows: 8) Two paths $P_1$ and $P_2$ with common nodes are randomly selected from the population according to the crossover probability $P_c$; 9) From all the common nodes in $P_1$ and $P_2$ (except the source and endpoints), a node is randomly selected as the crossing position; 10) All subpaths after cross positions are exchanged.

![FIGURE 2. Schematic diagram of path crossing](image)

1) According to the mutation probability $P_m$, a path $P$ is randomly selected from the population, and an intermediate node is randomly selected as the mutation location; 2) A new node is selected randomly from all the neighbours of the mutation node; 3) Using the variable weight method, the shortest subpath from the new node to the destination is calculated according to the Dijkstra algorithm; 4) The source node is linked to the mutation node, the mutation node is linked to its neighbour's new node, and the new node is linked to the destination node to form a new route. In case of mutation, the Dijkstra algorithm is executed once; Each path of the above initial population and the new path generated by crossover and mutation mechanism ensure the avoidance of the loop.

Step 3: a group of non-inferior paths in the external set provided in step 2 is taken as the final route. The principle of routing selection is to select routes adaptively according to the needs of communication services. According to step 2, these routes meet the constraints, that is, they are all feasible paths [20]. For example, for services with high real-time requirements, the path with the lowest $\text{Delay}(P)$ is selected. According to the nature of the non-inferior path, another performance index of the selected path is also excellent. In addition, other unselected non-inferior paths in the external set of genetic algorithms (GA) can also be used as backup schemes in the routing table, to enable them in case of network congestion or accident.

III. RESULTS AND ANALYSIS

The experiments on testing the simulation performance of the proposed algorithm are implemented on PC, and the specific configuration environment information is shown in Table 1.

| TABLE I CONFIGURATION ENVIRONMENT INFORMATION | Information |
|----------------------------------------------|-------------|
| Configuration type                           | Information |
| Processor                                     | Intel® Celeron® CPU G1620@16GHz |
| Operating system                             | Windows 10 |
| Install memory                               | 16GB |
| Compiler                                     | Microsoft Visual Studio 2013 |
| Development language                         | C++ |

A. Average delay test

Testing the average delay changes of video, text and picture transmission in OBS network before and after using the algorithm in this paper, and the results are shown in Figure 3.
As shown in Figure 3, before and after using the proposed algorithm, the average delay of transmitting video, text and picture information in the OBS network is quite different. Before using the algorithm, the average delay of transmitting video, text and picture information in the OBS network is more than 600 ms, and after using the algorithm, the average delay of transmitting video, text and picture information in the OBS network is less than 500 ms. It is verified that after the algorithm is used, the transmission speed of video, text and picture in the OBS network is optimized. The algorithm in this paper has better searchability, finds better information forwarding routes, makes the network topology very stable and changes little, and reduces the average delay of data packets from the source node to the target node.

B. Packet delivery rate

Testing the change of packet delivery rate of video, text and picture transmitted by OBS network before and after using the algorithm in this paper, and the results are shown in Figure 4.

As shown in Figure 4, before and after using the proposed algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are quite different. Before using the algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are quite different. Before using the algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are quite different. Before using the algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are quite different.
the algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are all less than 90%. After using the algorithm, the packet delivery rates of video, text and picture transmitted by the OBS network are all more than 95%. It is verified that after the algorithm is used, the packet delivery rate of video, text and picture in the OBS network can be improved. The algorithm can establish an ideal data forwarding route, reduce the packet loss rate of data, and ensure the reliability of packet forwarding.

C. Blocking probability
Network blocking probability reflects the criterion for a service to obtain a reliable connection in the network. It is the ratio of the number of routing requests that the routing algorithm fails to find a feasible path to the total number of simulated requests. It is one of the most commonly used methods to evaluate the performance of routing algorithms. Testing the change of blocking probability of video, text and picture transmitted by OBS network before and after using the proposed algorithm, and the results are shown in Figure 5.

As shown in Figure 5, the packet delivery rate of video, text and picture transmitted by the OBS network before and after using the proposed algorithm is quite different. Before using this algorithm, the blocking probability of video, text and picture transmitted by the OBS network is relatively large, which is more than 0.10. After using this algorithm, the blocking probability of video, text and picture transmitted by the OBS network is always controlled within 0.10, which verifies that the algorithm can always keep a very low blocking probability, so it has good scalability.

D. Use cost
The cost of transmitting video, text and pictures in the OBS network before and after using the proposed algorithm is tested. The results are shown in Table 2.

According to the analysis of Table 2, before using the proposed algorithm, the maximum cost of transmitting video, text and picture information in the OBS network is 1654 yuan, 897 yuan and 789 yuan respectively. After using the proposed algorithm, the maximum cost of transmitting video, text and picture information in the OBS network is less than 510 yuan, and the cost is significantly reduced. Thus, the proposed algorithm can establish a more ideal data forwarding route, and reduce the number of information transmissions and the cost of information transmission.

E. Fault location effect of transmission link in OBS Network
The sample size of transmission information in the OBS network is set to 100, 200, 300, 400, 500 in turn [21,22]. Under this condition, the positioning effect of the proposed algorithm on
transmission link fault in the OBS network is tested. The positioning effect is mainly reflected by recall and precision. The results are shown in Figure 6.

As shown in Figure 6, after locating the transmission link fault of the OBS network, the recall rate and precision rate of the fault locating are as high as 0.98, and the positioning accuracy is very high. This has a positive effect on the QoS routing optimization efficiency of the OBS network, which can effectively lock the optimization range and reduce idle work.

![Recall ratio](image1)

![Precision ratio](image2)

**FIGURE 6. Test results of recall and precision of the algorithm**

**IV. CONCLUSION**

With the rapid development of network and application services, the QoS routing optimization algorithm has increasingly become one of the core issues in optical burst switching networks. Multi constraint routing plays an important role in QoS architecture. Based on the idea of multi-objective optimization, this paper transforms the multi constraint routing problem into a constrained multi-objective routing optimization problem, proposes a QoS routing optimization algorithm for optical burst switching networks based on multi-objective genetic algorithm, and analyzes the application effect of this multi-objective routing algorithm, It solves the problems existing in traditional algorithms and lays the foundation for optical burst switching network services. It is hoped that this research can provide a certain value reference for related research. This algorithm has the following advantages:

1. After using this algorithm, the average delay of transmitting video, text and picture in optical burst switching network is less than 400ms, the packet delivery rate is greater than 95%, the blocking probability is always controlled within 0.10, the maximum use cost is less than 510 yuan, and the recall and precision of transmission link failure in optical burst switching network are as high as 98%.

2. This algorithm can improve the packet delivery rate of the optical burst switching network, reduce the transmission delay, blocking probability and use cost of the optical burst switching network, and optimize the service quality of the optical burst switching network. Using a constrained multi-objective genetic algorithm is an effective way to solve multi-constrained routing, which plays an important role in improving network performance.

The QoS routing optimization of optical burst switching networks needs to be further studied in the following aspects.

**A. Information Obsolescence**

The obsolescence of state information is inevitable in the actual network and will have a significant impact on the performance and effectiveness of service quality in the OBS network. However, the analysis of this obsolescence involves complex stochastic mathematical models, and the related discussions are often based on simulation test data but lack quantitative theoretical analysis. In addition, the usual algorithms only stay in the theoretical design and analysis, lacking consideration of the actual performance of the algorithm in the case of old information. Therefore, it can be considered to solve the problem based on the probability model to find the feasible path with the maximum probability to meet the QoS constraints, to effectively reduce the additional burden on the network caused by connection failure.

**B. Multi route and rerouting**

In the method of detecting feasible paths on multiple possible paths at the same time, how to combine with resource reservation has no conclusion. In addition, the OBS network provides multiple paths from source to destination, and multiplexes these paths in parallel, which is transparent to user services. This is a multiplex routing method. However, the main problem is how to synchronize multiple paths, and how to avoid packet delay jitter and disorder. Due to the unreasonable allocation of network resources and feasible paths, rerouting is required in some cases. Rerouting can be carried out when the network resources are insufficient, which can effectively reallocate the network resources. However, due to the problems of state preservation, synchronization and overhead, rerouting becomes very difficult.
C. Integration with other network components

The future network should be the combination of the OBS network and other network components. The goal of network routing is to maximize resource utilization, which includes accepting as many QoS connection requests as possible, and maximizing the throughput and response speed of services. Because the two are contradictory, there are many problems in the process of their integration. For example, when the link with resource reservation is idle, the link without resource reservation may cause congestion due to best-effort service. This kind of congested link may still accept QoS requests because it has no reserved resources. In addition, the QoS routing optimization algorithm of the OBS network must be combined with other network components to provide a QoS guarantee, including state collection, resource reservation, packet scheduling and so on. Therefore, the simplification of the OBS network and other network components can be considered.

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