IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 29, 2021, accepted December 17, 2021, date of publication December 24, 2021,
date of current version February 2, 2022.

Digital Object Identifier 10.1109/ACCESS.2021.3138380

QoS Routing Algorithm for OBS Networks Based on a Multi-Objective Genetic Algorithm

LI-SHENG CUI[1] AND GAUTAM SRIVASTAVA[2,3], (Senior Member, IEEE)
[1]Department of Mathematics and Computer Science, Xinyang Vocational and Technical College, Xinyang 464000, China
[2]Department of Mathematics and Computer Science, Brandon University, Brandon, MB R7A 6A9, Canada
[3]Research Centre for Interneural Computing, China Medical University, Taichung 404, Taiwan

Corresponding author: Gautam Srivastava (srivastavag@brandonu.ca)

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, telemedicine, 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.

The associate editor coordinating the review of this manuscript and approving it for publication was Zhaojun Li.

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].

As the basic technology of the next generation optical Internet, the OBS network 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 negative ideal object determines the distance between the object to be evaluated and the positive ideal object and negative ideal object, and uses the score function value to define the fuzzy value of the qualitative index, then obtains the evaluation value of the object to be evaluated by the weighting method, and realizes the QoS routing optimization of wireless sensor networks according to the value. 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. According to the service nature, the path is configured adaptively to optimize the quality of service 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.

B. 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, $P_{F\times S} = (0, 1)$.

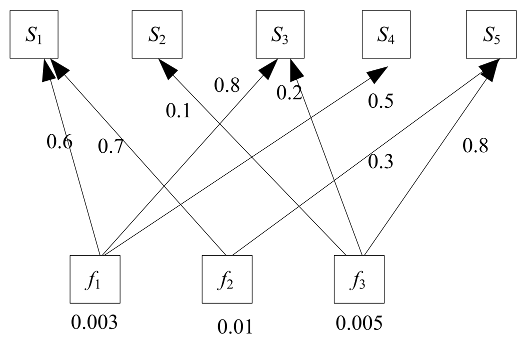


FIGURE 1. Probability weighted bipartite graph.

To better study, the probability-weighted bipartite graph, the parameters $F(S_i)$, $S(f_t)$ and S_O are defined. $F(S_i)$ represents the set of all transmission link failures associated with symptoms S_i; $S(f_t)$ represents the set of all transmission link failures associated with symptoms f_t; 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 $p(f_t|S_i)$ in turn. $p(f_t|S_i)$ is the probability of fault f_t under the condition of symptom S_i. The larger the $p(f_j|s_t)$ value is, the more likely the transmission link fault f_t is to explain the symptom S_i.

$$p(f_t|S_i) = \frac{p(f_t)\,p(f_t|S_i)}{\sum_{f\in F(S_i)} p(f_t)\,p(f_t|S_i)} \tag{1}$$

where $p(f_t)$ is the probability of transmission link failure without symptoms.

2) NORMALIZATION OF BAYESIAN PROBABILITY INFORMATION

For different transmission link faults, $f_t \in F(S_i)$ and $p(f_t|S_i)$ values are different, so different $f_t \in F(S_i)$ has a different explanation for symptom S_i. After normalization calculation, the explanation degree $a(f_t, S_i)$ of fault f_t 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_t 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_t is defined as $a(f_t, S_i)$. From a statistical point of view, the value of $a(f_t, S_i)$ can be interpreted as the number of symptoms S_i of transmission link failure f_t.

$$a(f_t, S_i) = \frac{p(f_t|S_i)}{\sum_{f\in F(S_i)} p(f_t|S_i)} \tag{2}$$

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.

$$a(f, S_N) = \sum_{f\in F(S_i)} p(f_t|S_i) \tag{3}$$

C. 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 $a(f_t, S_i)$ 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 $a(f, S_N)$ of each possible fault to symptom set S_N. According to the size $a(f, S_N)$, 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_a and the elements F_a are sorted from large to small. When the most likely first m transmission link failures F_a completely cover all the observed symptom sets S_N, it is considered that the optimal transmission link failure hypothesis set is found.

If a transmission link failure of multiple independent optical burst switching networks causes a symptom, any transmission link failure may cause the 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_O; symptom set $S_N \subseteq S_O$ observed in a single time window; symptom observable rate $OR\,(OR = S_O/S)$; 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 $F(S_N)$ to be selected;

Step 3. For each fault f_t in $F(S_N)$, $a(f_t, S_i)$ is calculated and added to set F_a;

Step 4. The initialization symptom set S_a is empty;

Step 5. The explanation degree of symptoms in the set F_a is sorted from high to low, and $a \in F_a$ F is taken out, in turn, to execute until $|S_a \cap S_N| / |S_N| = 1$;

Step 5.1 The corresponding f_t of a is obtained;

Step 5.2 The corresponding S_i of f_t is obtained;

Step 5.3 If $S_a \cup S_N - S_a \neq \emptyset$, $H = H \cup \{f_t\}$;

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

D. 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 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.

E. 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-objectives, 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 [15]. 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. $Bandwidth_0$ and $Loss_0$ 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:

$$\min imizeF\,(P) = \left(\sum_{i\in P} Cost\,(i)\,, \sum_{i\in P} Delay\,(i)\right) \tag{4}$$

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

$$Bandwidth\,(P) = \min_{i\in P}\,[Bandwidth\,(i)] \geq Bandwidth_0 \tag{5}$$

$$Loss\,(P) = 1 - \prod_{i\in P} (1 - Loss\,(i)) \leq Loss_0 \tag{6}$$

where, $Bandwidth\,(P)$ and $Loss\,(P)$ 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 subtargets in the target $F\,(P)$ are minimized at the same time.

The characteristics of multi-objective optimization lie in the incommensurability 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.

F. 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 generate the 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 find the shortest path according to the aggregation of a single metric. At this time, the link i weight becomes:

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

where, α and β 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 α and get the corresponding β, 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 ρ, and an empty auxiliary external population set ρ' 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 *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 *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 $Fitness = n/\rho$ 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.

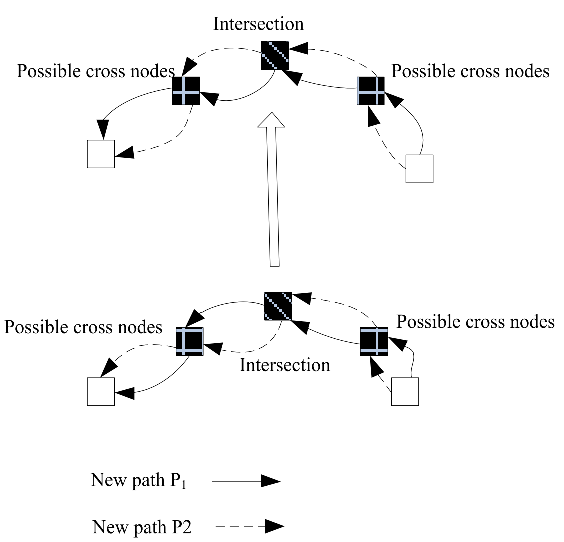


FIGURE 2. Schematic diagram of path crossing.

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 $Const\,(P)$ of a path P is:

$$Const\,(P) = 100.0 \times |Loss\,(P) - Loss_0| + |Bandwidth\,(P) - Bandwidth_0| \quad (8)$$

The genetic operation of an information transmission path in an OBS network includes path crossover and path mutation, which is an 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:

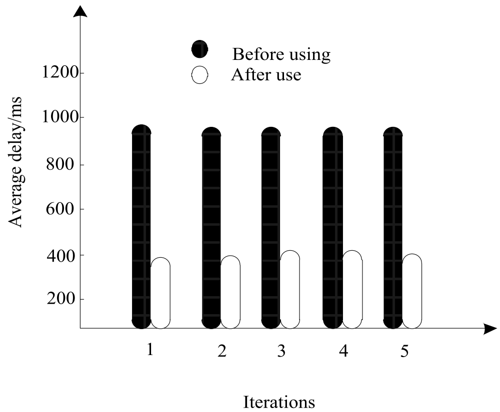
1) Two paths P_1 and P_2 with common nodes are randomly selected from the population according to the crossover probability P_c;
2) From all the common nodes in P_1 and P_2 (except the source and endpoints), a node is randomly selected as the crossing position;
3) All subpaths after cross positions are exchanged.

TABLE 1. Configuration environment information.

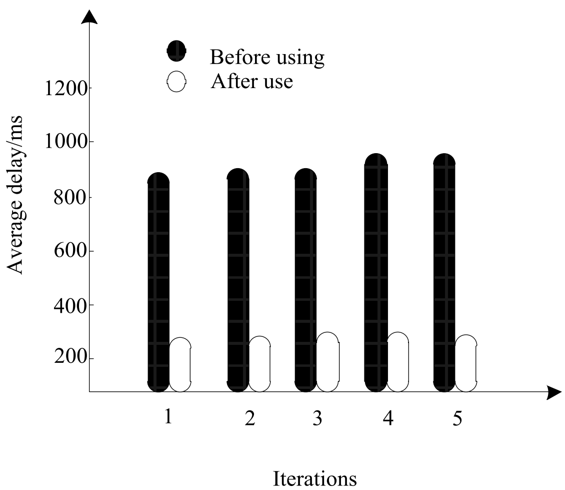
Configuration type	Information
Processor	Intel® Celeron® CPU G1620@16GHz
Operating system	Windows 10
Install memory	16GB
Compiler	Microsoft Visual Studio 2013
Development language	C++

For example, the following two paths are crossed: $P_1 = (0, 1, 3, 5, 7, 8, 9, 10)$, $P_2 = (0, 2, 3, 4, 6, 8, 10)$. The nodes in the blank grid in the figure are optional crossing positions. If 8 is selected as the crossing point, the new individuals will change to $P_1 = (0, 1, 3, 5, 7, 8, 10)$ and $P_2 = (0, 2, 3, 4, 6, 8, 9, 10)$. Path mutation is to form a new path by randomly disturbing the existing path and the steps are as follows:

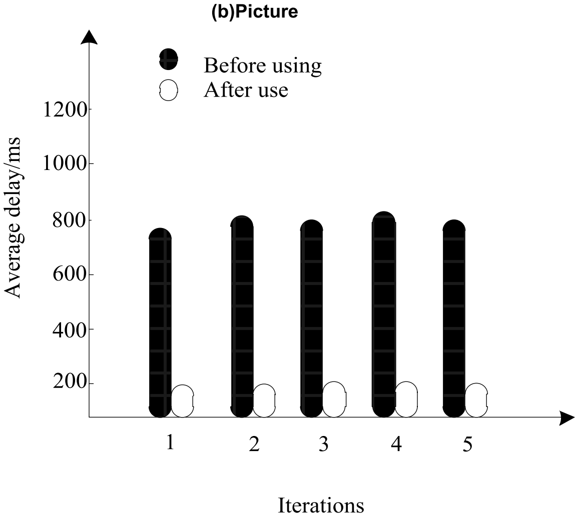
1) According to the mutation probability P_m, a path P is randomly selected from the population, and an intermediate node is randomly selected as the mutation location;
2) A new node is selected randomly from all the neighbours of the mutation node;
3) Using the variable weight method, the shortest subpath 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;



(a)Video



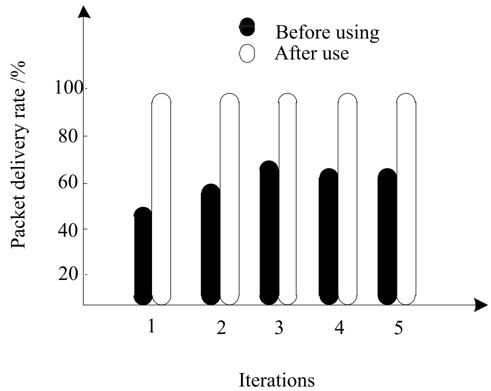
(b)Picture



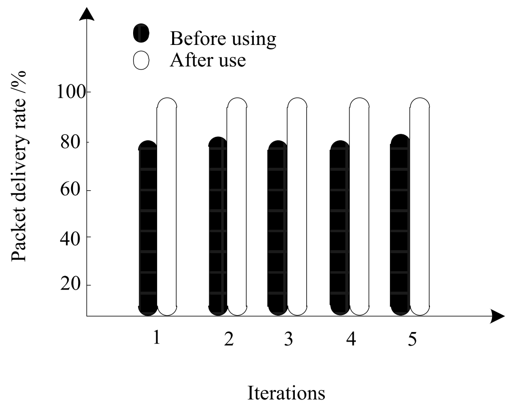
(c)Written words

FIGURE 3. The average delay change of optical burst switching network before and after the algorithm used.

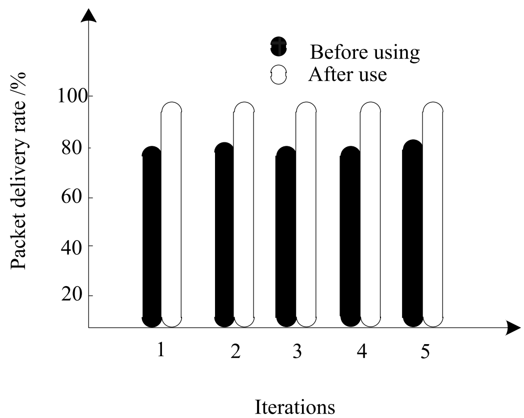
Each path of the above initial population and the new path generated by crossover and mutation mechanism ensure the avoidance of the loop.



(a)Video



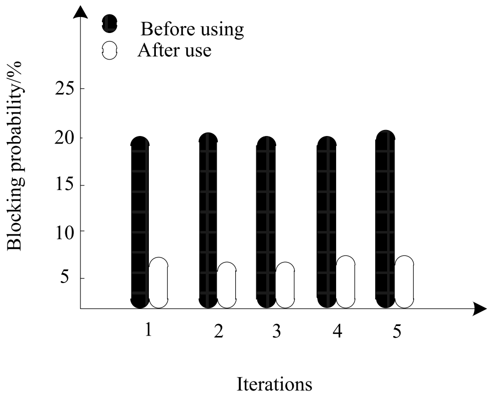
(b)Picture



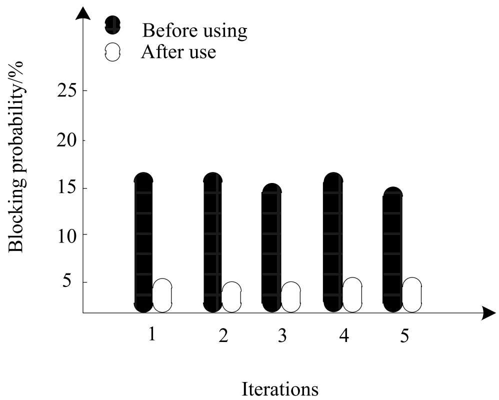
(c)Written words

FIGURE 4. The change of packet delivery rate of video, text and picture transmitted by OBS network before and after using the algorithm.

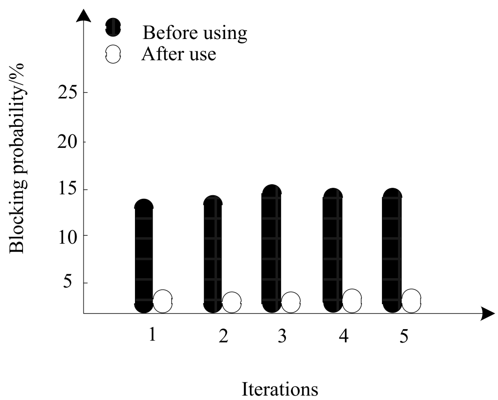
Step 3: a group of non-inferior paths in the external set provided in step 2 is taken as the final route. The principle of routing selection is to select routes adaptively according to the needs of communication services. According to step 2, these routes meet the constraints, that is, they are all feasible paths [20]. For example, for services with high real-time requirements, the path with the lowest *Delay* (P) is selected. According to the nature of the non-inferior path, another



(a)Video



(b)Picture



(c)Written words

FIGURE 5. **The change of blocking probability of video, text and picture transmission in the OBS network before and after using the algorithm.**

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.

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.

TABLE 2. **The cost of transmitting video, text and pictures on the OBS network before and after the use of the algorithm.**

Iterations	Before			After		
	Video	Picture	words	Video	Picture	words
1	1454	865	765	503	432	342
2	1345	897	786	501	434	345
3	1654	887	789	503	445	345
4	1546	856	776	503	421	332
5	1453	891	756	502	412	311

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 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.

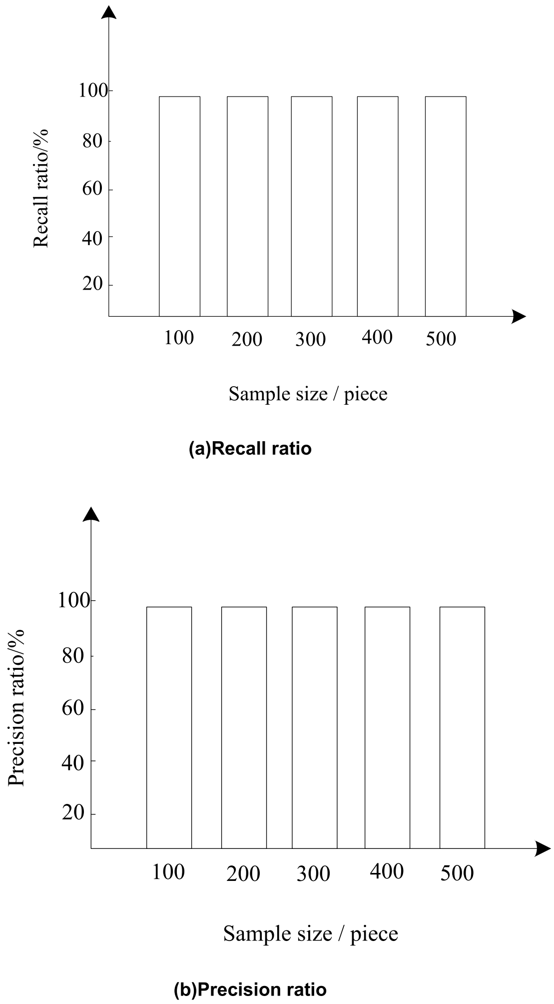


FIGURE 6. Test results of recall and precision of the algorithm.

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.

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.

REFERENCES

[1] S. Manisekar and J. A. V. Selvi, "An enhanced proactive transmission protocol for optical burst switching networks," *Appl. Math. Inf. Sci.*, vol. 13, no. 1, pp. 87–96, Jan. 2019.

[2] R. S. Barpanda, A. K. Turuk, and B. Sahoo, "QoS aware routing and wavelength allocation in optical burst switching networks using differential evolution optimization," *Digit. Commun. Netw.*, vol. 4, no. 1, pp. 3–12, 2018.

[3] M. K. Hossain and M. M. Haque, "Semi-supervised learning approach using modified self-training algorithm to counter burst header packet flooding attack in optical burst switching network," *Int. J. Elect. Comput. Eng.*, vol. 10, no. 4, pp. 4340–4351, 2020.

[4] V. K. Kumar, K. S. Reddy, and M. N. Prasad, "POCS-VF: Proximate optimum channel selection through void filling and burst to segment for burst scheduling in OBS networks," *J. Theor. Appl. Inf. Technol.*, vol. 96, no. 4, pp. 1091–1101, 2018.

[5] J. Wu, L. Wang, and H. Y. Shi, "An evaluation method of quality of service (QoS) for wireless sensor networks," *J. Qiongzhou Univ.*, vol. 25, no. 5, pp. 80–85, 2018.

[6] X. D. Shi, Y. J. Li, S. H. Zhao, W. L. Wang, and X. Y. Wang, "Multi-QoS target optimization routing algorithm for satellite network based on SDN," *Syst. Eng. Electron. Technol.*, vol. 42, no. 6, pp. 1395–1401, 2020.

[7] V. M. N. Vo, T. D. Pham, T. C. Dang, and V. H. Le, "A mechanism of QoS differentiation based on offset time and adjusted burst length in OBS networks," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 28, no. 5, pp. 2808–2820, Sep. 2020.

[8] S. Verma, N. Sood, and A. K. Sharma, "QoS provisioning-based routing protocols using multiple data sink in IoT-based WSN," *Mod. Phys. Lett. A*, vol. 34, no. 29, pp. 197–211, 2019.

[9] S. Liu, D. Liu, K. Muhammad, and W. Ding, "Effective template update mechanism in visual tracking with background clutter," *Neurocomputing*, vol. 458, pp. 615–625, Oct. 2021.

[10] X. Liu, S. Chen, L. Song, M. Woźniak, and S. Liu, "Self-attention negative feedback network for real-time image super-resolution," *J. King Saud Univ.-Comput. Inf. Sci.*, early access, pp. 1–8, Jul. 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1319157821001816?via%3Dihub, doi: 10.1016/j.jksuci.2021.07.014.

[11] S. AlQahtani and A. Alotaibi, "A route stability-based multipath QoS routing protocol in cognitive radio ad hoc networks," *Wireless Netw.*, vol. 25, no. 5, pp. 2931–2951, Jul. 2019.

[12] A. S. Yeremenko, "A two-level method of hierarchical-coordination QoS-routing on the basis of resource reservation," *Telecommun. Radio Eng.*, vol. 77, no. 14, pp. 1231–1247, 2018.

[13] J. Agarkhed, V. Kadrolli, and S. R. Patil, "Fuzzy clustering with multi-constraint QoS service routing in wireless sensor networks," *J. Telecommun. Inf. Technol.*, vol. 1, pp. 31–38, Apr. 2019.

[14] A. R. Kumar and A. Sivagami, "Trust-based routing protocol for QoS optimization in cluster-based WMSN," *J. Adv. Res. Dyn. Control Syst.*, vol. 10, no. 12, pp. 66–78, 2018.

[15] S. Ahmed, N. V. K. Ramesh, and B. N. K. Reddy, "A highly secured QoS aware routing algorithm for software defined vehicle ad-hoc networks using optimal trust management scheme," *Wireless Pers. Commun.*, vol. 113, no. 4, pp. 1807–1821, 2020.

[16] R. S. Abujassar, "Developing QoS by priority routing for real time data in Internet of Things (IoT) urban scenarios," *Int. J. Comput. Netw. Commun.*, vol. 11, no. 6, pp. 45–61, 2019.

[17] M. Ghafouri Vaighan and M. A. Jabraeil Jamali, "A multipath QoS multicast routing protocol based on link stability and route reliability in mobile ad-hoc networks," *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 1, pp. 107–123, Jan. 2019.

[18] C. J. Sui and H. Li, "Neural network clustering routing algorithm based on genetic optimization," *Commun. Technol.*, vol. 52, no. 1, pp. 101–105, 2019.

[19] A. Notom, S. Mrinal, and P. Parag, "Systematic-RLNC based secure and QoS centric routing scheme for WSNs," *J. Telecommun. Inf. Technol.*, vol. 4, no. 2019, pp. 55–64, Jan. 2020.

[20] S. Y. Chen and Y. Xia, "Service quality control simulation in heterogeneous converged networks," *Comput. Simul.*, vol. 37, no. 3, pp. 364–367, 2020.
[21] W. Fu, S. Liu, and G. Srivastava, "Optimization of big data scheduling in social networks," *Entropy*, vol. 21, no. 9, p. 902, Sep. 2019.
[22] S. Lou, G. Srivastava, and S. Liu, "A node density control learning method for the Internet of Things," *Sensors*, vol. 19, no. 15, p. 3428, 2019.

LI-SHENG CUI was born in Luoshan, Xinyang, China, in 1988. He received the bachelor's degree from the College of Computer Science and Technology and Information Engineering, Chinese People's Liberation Army Strategic Support Force, in 2008, and the master's degree from the College of Computer Science and Technology, Chengdu University of Technology, in 2011.

Since 2013, he has been serving as a Lecturer with the School of Mathematics and Computer Science, Xinyang Vocational and Technical College. He published over ten papers on the directions of computer application technology.

Mr. Cui has won second place in the Third Young Teacher Competition and in the Courseware Production, and was an Excellent Employee of the new media operation of the university.

GAUTAM SRIVASTAVA (Senior Member, IEEE) received the B.Sc. degree from Briar Cliff University, USA, in 2004, and the M.Sc. and Ph.D. degrees from the University of Victoria, Victoria, BC, Canada, in 2006 and 2011, respectively.

He taught for three years at the Department of Computer Science, University of Victoria, where he was regarded as one of the top undergraduate professors in the computer science course instruction at the university. In 2014, he joined a tenure-track position at Brandon University, Brandon, MB, Canada, where he is active in various professional and scholarly activities. He was promoted to an Associate Professor, in January 2018. He is active in research in the fields of data mining and big data. In his eight years of academic career, he has published a total of 43 papers in high-impact conferences and high-status journals (SCI, SCIE) and has also delivered invited guest lectures on big data, cloud computing, the Internet of Things, and cryptography at many Taiwanese and Czech universities.

Prof. Srivastava received the Best Oral Presenter Award in FSDM 2017, which was held at the National Dong Hwa University (NDHU), Shoufeng, Hualien, Taiwan (Republic of China), in November 2017. He is an Editor of several international scientific research journals. He currently has active research projects with other academics in Taiwan, Singapore, Canada, Czech Republic, Poland, and USA.