Model of Optimal Paths Design for GMPLS Network and Evaluation of Solution

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Abstract: - We describe an optimal path design for a GMPLS network that employs the Lagrangian relaxation method, which can be used to estimate the lower bounds of a solution to a problem. This feature assists the designer of the problem to consider the accuracy of the solution obtained by the calculation when deciding whether to assign the solution to a real network in critical situations. A formulation of the problem and how to solve it using the Lagrangian relaxation method is described, and the results obtained by a prototype and considerations are shown in this paper.

Key Words: - Optimal path design, GMPLS, Lagrangian relaxation, Heuristic algorithm, Simulation, Lower bound, Practical approximate solution, Emergencies

1 Introduction

Remarkable progress has been made on the Internet. Both the bandwidth and the scale of networks have been increased greatly. The core network of the Internet is evolving. The physical network architecture employs wavelength-routing switches at routing nodes, which enable the establishment of circuit-switched, all-optical, wavelength-division multiplexed (WDM) channels, which are referred to as paths. The virtual topology consists of a set of such paths, and they may be used to transport packet-switched traffic through the network. Generalized multiprotocol label switching (GMPLS) is a technology that enhances multiprotocol label switching (MPLS), enabling it to support network switching for time, wavelength, and space switching, as well as for packet switching [1-2].

GMPLS is extended from MPLS technology that determines path routing by adding packets. This extended technology determines path routing by considering optical network signals having wavelength labels $ë_i$ [3-4], as shown in Fig. 1. The large-capacity, high-speed optical network shown in Fig. 2 has almost been turned into reality by using WDM technology, GMPLS technology, and optical cross-connect switches that switch optical signals as they are.

A prototype of a policy-based management system for MPLS Traffic Engineering is operating on MPLS network elements [5]. One study has presented a technique that enables guarantee of service (GoS) to privileged information flows [6]. In the network for GMPLS, the paths, which have to be set beforehand, are essentially static. Finding effective techniques for designing the virtual topology of the paths is a significant problem for successful networking [7-10].

If a new path-setting request is generated, GMPLS technology calculates paths using the Constrained Shortest Path First (CSPF) algorithm from the link information of a band collected by the optical cross-connect switches and the path congestion status and determines paths that minimize the congestion [11-12]. This technology thus enables optimal paths to be set by adding new paths to existing ones at path calculation by CSPF, but it cannot be used to optimize an entire GMPLS network. Therefore, GMPLS cannot make optimal use of network resources and the utilization efficiency can still be further improved.

This problem of increasing the utilization efficiency of network resources has been formulated as an optimization problem with the constraints of conservation of flow and capacity

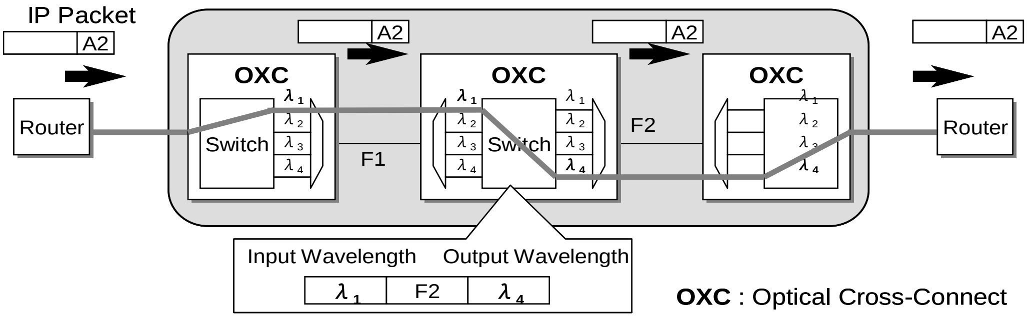

Fig. 1 Network switching by MPLS technology

restriction to disperse the line load. Attempts have been made to solve this problem.

The key objectives in designing the paths for GMPLS are to achieve the requested specifications that link one source node to the other terminal mode of the network and to achieve a sufficient rest margin for the network capacity to enable alternative paths to be found in the case of an emergency. Therefore, the problem of path design for GMPLS can be formulated as an optimization problem that aims to achieve the most efficient use of network resources [13-15]. However, this type of optimization problem is generally known to be an NP-hard problem [16-17], and probabilistic search algorithms or heuristic algorithms are often applied to the problem to obtain practical approximate solutions [18-20], which are not guaranteed to be optimal. Furthermore, there are no means to measure how far the solutions obtained by these algorithms are from the optimal one. This is not a serious problem for typical network management problems, since in those cases there is sufficient time to search for such practical approximate solutions. In emergencies, however, it is important to evaluate the gap between such practical approximate solutions and the optimal solution because of the penalty cost that network carriers have to pay, which depends on the degree of actual damage sustained by customers.

This paper assumes the three operational phases depicted in Fig. 3. In the first phase (the initial phase), the initial path design is created. In the second phase (the incremental phase), individual paths based on the shortest path of the CSPF algorithm are set to satisfy the daily incremental path setting requests. In the third phase (the repacking phase), in which the utilization of network resources has begun to decline, the path design optimization problem, which addresses all path-setting requests by network operators, is solved. Path design by the conventional CSPF algorithm belongs to the second phase. This paper describes optimal paths design in the third phase (the repacking phase).

We present a formulation of such an optimization problem for the paths design of a GMPLS network and an algorithm that solves it and evaluates the gap between the practical approximate solution and the optimal solution using the Lagrangian relaxation method [21-22]. The Lagrangian relaxation method determines the lower bound of feasible solutions for the optimization problem using a heuristic search. We can therefore determine the gap between them even

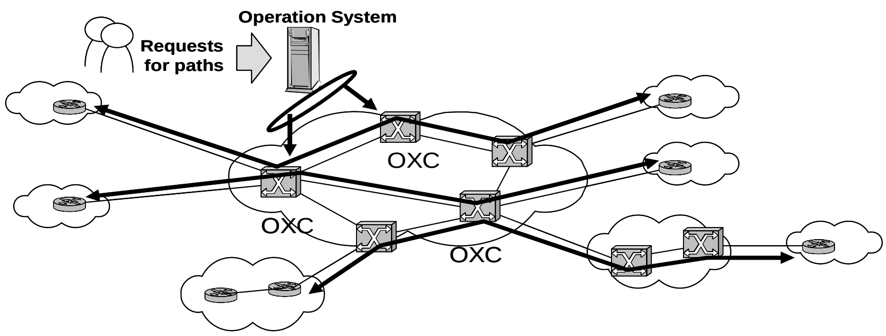

Fig. 2 Structure of optical network

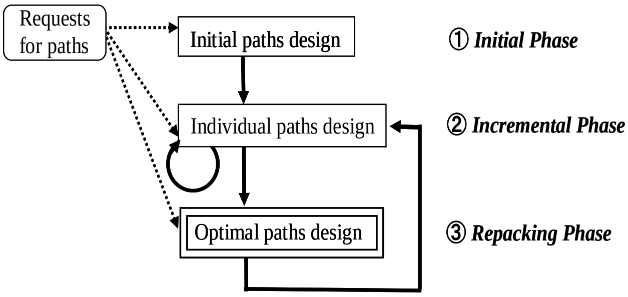

Fig. 3 Three operational phases for optimal path design method

if we break the calculation of the optimization problem at any time before the optimal solution is found.

We can hereby evaluate the gap to determine if it is still possible to improve the solution, and we can judge whether or not to assign the paths obtained by the calculation to the actual network.

In the next section, we describe the formulation of the optimization problem, which is the optimal path design for the GMPLS network, and in Section 3 we present a way to solve the problem using the Lagrangian relaxation method. We then present our results for sample cases and mention some considerations.

2 Formulation of the Problem

The optical signals of the traffic are switched by optical routers for the GMPLS network according to the wavelength of the light, and all of the paths from the source nodes to the terminal nodes have to be set correspondingly. However, if you assign the shortest paths from the source nodes to the termination nodes without careful consideration, the network resources will be under utilized, and the addition of new paths or the provision of alternative paths might be difficult in the event of network trouble. Therefore, you should assign the most appropriate paths rather than the shortest paths.

As an example, Fig. 4 depicts the optimal path problem when there are seven path setting requests for an optical network that consists of four optical lines linking five optical cross-connect switches that act as nodes. On the left side of Fig. 4, the shortest path is simply assigned for each path-setting request. In this case, only six path-setting requests can be accommodated and the remaining one cannot. On the right side of Fig. 4, however, the shortest path is not assigned for two of the requests. Instead, a detour circuit that is one hop longer is assigned; this enables all seven requests to be accommodated.

In this section, we describe the formulation for this as an optimization problem, using principles from multicommodity flow for the physical routing of paths.

We adopt the following notation. i denotes a node (i.e., a network router) and N denotes a set of nodes. j denotes a branch between two nodes (i.e., an optical line in the network), and E denotes a set of branches. r denotes a request to link a source node to a termination node, and R denotes a set of requests. $s(r)$ and $t(r)$ denote the source and termination nodes of request r, respectively. x_j^r, which is a variable to be determined, is 1 if the request r uses branch j, and is 0 if the request r does not use branch j. u_j denotes the capacity of branch j. $A^-(i)$ denotes a set of branches, the start node of which is i, and $A^+(i)$ denotes a set of branches, the destination node of which is i.

The optimization problem of this paper can be described by using the flow conservation law and the constraint conditions for the optical lines.

(P1)

$$\min_x \quad f(x) \tag{1}$$

$$\text{s.t.} \quad \sum_{j\in A^-(i)} x_j^{\,r} - \sum_{j\in A^+(i)} x_j^{\,r} = b_i^r \tag{2}$$

$$\sum_{r\in R} x_j^{\,r} \le u_j \tag{3}$$

$$x_j^{\,r} \in \{0,\ 1\} \tag{4}$$

Here, b_i^r, which is a constant, is 1 when i is equal to $s(r)$, -1 when i is equal to $t(r)$, and 0 otherwise. $f(x)$ is an appropriate cost function of the problem that avoids an over concentration of paths to particular branches. We use the function defined in equation (5) to equalize the consumption ratios of each branch.

$$f(x) = \sum_{j\in E} \left| \frac{\sum_{r\in R} x_j^{\,r}}{u_j} \right|^2 \tag{5}$$

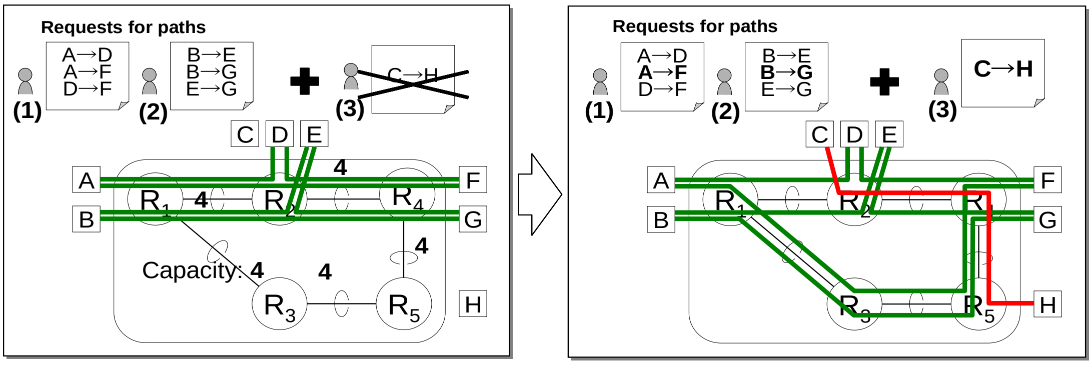

Fig. 4 Example of the optimal paths design for GMPLS network

3 Solution using the Lagrangian Relaxation Method

We apply the Lagrangian relaxation method to the optimal paths design problem described in Section 2. It determines the lower bound of the problem.

The Lagrangian relaxation method performs a heuristic search to determine a feasible solution, but it is also able to simultaneously obtain a lower bound (for a minimization problem). Even when the optimization problem is aborted, it is still possible to know the deviation between the lower bound and the accuracy of solution [23].

The Lagrangian relaxation method uses Lagrange multipliers to reduce part of the constraint conditions by including the conditions in the cost function. This divides the original problem (i.e., the primary problem) into subproblems that are independent of the respective of the variables. The optimal solution is obtained by solving its dual problem. To divide the problem (P1), we introduce artificial variables, v_j, which indicate the number of remaining wavelengths that can be assigned in the line, and we transform problem (P1) into problem (P2).

(P2)

$$\min_{v} \quad g(x)=\sum_{j\in E}\left|\frac{u_j-v_j}{u_j}\right|^2 \tag{6}$$

$$\text{s.t.} \quad \sum_{j\in A^-(i)} x_j^{\,r} - \sum_{j\in A^+(i)} x_j^{\,r} = b_i^{\,r} \tag{7}$$

$$\sum_{r\in R} x_j^{\,r} + v_j \le u_j \tag{8}$$

$$x_j^{\,r} \in \{0,\ 1\} \tag{9}$$

$$0 \le v_j \le u_j \tag{10}$$

We then use Lagrange multipliers, $\lambda_j > 0 \ (j=1,\ldots m)$, to relax the equation (8), and obtain the Lagrangian relaxation problem (P3).

(P3)

$$\min_{v,x} \quad h_\lambda(v,x) \tag{11}$$

$$\text{s.t.} \quad \sum_{j\in A^-(i)} x_j^{\,r} - \sum_{j\in A^+(i)} x_j^{\,r} = b_i^{\,r} \tag{12}$$

$$x_j^{\,r} \in \{0,\ 1\} \tag{13}$$

$$0 \le v_j \le u_j \tag{14}$$

where function h is as follows.

$$h_\lambda(v,x)=p_\lambda(v)+q_\lambda(x)+c \tag{15}$$

$$p_\lambda(v)=\sum_{j\in E}\left[\left\{z_j-\left(1-\frac{\lambda_j u_j}{2}\right)\right\}^2-\left(1-\frac{\lambda_j u_j}{2}\right)^2\right] \tag{16}$$

$$q_\lambda(x)=\sum_{r\in R}\sum_{j\in E}\lambda_j x_j^{\,r}=\sum_{r\in R} q_\lambda^{\,r}(x^r) \tag{17}$$

$$c=m-\sum_{j\in E}\lambda_j u_j = \text{const.} \tag{18}$$

$$z_j=\frac{v_j}{u_j} \tag{19}$$

In this way, we can divide this Lagrangian relaxation problem (P3) into two subproblems, which are independent of v_j (subproblem P4) and x_j (subproblem P5).

(P4)

$$\min_{v} \quad p_\lambda(v) \tag{20}$$

$$\text{s.t.} \quad 0 \le z_j \le 1 \quad (z_j=\frac{v_j}{u_j}) \tag{21}$$

(P5)

$$\min_{x^r} \quad q_\lambda{}^r(x) \tag{22}$$

$$\text{s.t.} \quad \sum_{j\in A^-(i)} x_j{}^r - \sum_{j\in A^+(i)} x_j{}^r = b_i^r \tag{23}$$

$$x_j{}^r \in \{0,\ 1\} \tag{24}$$

Subproblem (P4) is just a simple problem to calculate the minimum value of the quadratic function, and subproblem (P5) is a problem to search for the minimum cost flow of a single commodity flow when the cost of branches is λ_j ; this is just a shortest path problem. Thus we can easily solve subproblem (P5) by using Dijkstra's algorithm.

We can then obtain the solution to the primary problem (P2) by solving the Lagrangian dual problem (P6), which is a maximization problem for the Lagrange multipliers.

(P6)

$$\max_{\lambda\ge 0} \left\{ \begin{array}{l} \min_{v,x} h_\lambda(v,x) \\ \quad = \min_v p_\lambda(v) + \sum_{r\in R} \min_{x^r} q_\lambda{}^r(x^r) + c \\ \text{s.t.} \quad 0 \le z_j \le 1 \quad (z_j = \dfrac{v_j}{u_j}) \\ \quad \sum_{j\in A^-(i)} x_j{}^r - \sum_{j\in A^+(i)} x_j{}^r - b_i^r \\ \quad x_j{}^r = \{0, 1\} \end{array} \right\} \tag{25}$$

$$\text{s.t.} \quad \lambda_j \ge 0 \tag{26}$$

By using subgradient optimization to improve the Lagrange multipliers for equation (27), we can find a good solution to the Lagrangian dual problem (P6).

$$\lambda^{n+1} = \lambda^n + T \frac{\partial h_{\lambda^n}(v,x)}{\partial \lambda} \tag{27}$$

Here, T is a parameter for adjusting the widths in order to improve the Lagrange multipliers. The improvement in the multipliers is repeated until the value of the cost function for the Lagrangian dual problem (P6), which is a lower bound of the primary problem, is equal to the value of the cost function for problem (P2), or until the difference between the two cost functions is sufficiently small.

We list the algorithm to solve the problem of the optimal path design for the GMPLS network below.

Algorithm
for the optimal path design problem

INPUT:
Set of nodes and branches (N, E)
Set of requests, R
Capacity of branches, u

OUTPUT:
Paths for requests

ALGORITHM:
Step 1: Initialize the Lagrange multipliers, λ_j .
Step 2: For a given λ_j *, calculate the solution to the Lagrangian relaxation problem (P4) and (P5), which is* $(v, x)_L$.
Step 3: Transform $(v, x)_L$ *to a feasible solution for the primary problem (P2) using the heuristic algorithm described below.*
Step 4: Calculate the value of the cost function for $g(v)$ *in equation (6) and* $h(\lambda, v, x)$ *in equation (11). If the difference between g and h is sufficiently small, or if the number of repetitions is sufficiently large, then finish this process.*
Step 5: Improve the Lagrange multipliers λ *by subgradient optimization and return to step 2.*

The heuristic algorithm used in Step 3 is as follows.

Paths p^r_L, which correspond to request r and are obtained as a solution to the Lagrangian relaxation problem, are transformed so as to be accepted in order of their lengths according to the following rules.

(1) If there are remaining wavelengths to be assigned in all the branches for path p^r_L*, let*

path $p^r{}_L$ be accepted without transformation as path $p^r{}_E$, which is a feasible path for the primary problem, and let the number of the remaining wavelengths of those branches be reduced.

(2) In cases except for (1), search for the shortest path, whose source and termination nodes are the same as $p^r{}_L$ for the network. If the shortest path can be found, it is accepted as the feasible path $p^r{}_L$.

(3) In cases except for (2), the network is divided into parts by the branches that have no remaining wavelength to be stored. First, select a path that has already been accepted and find its alternative path, which gives these branches remaining wavelength. Then, search for the shortest path, whose source and termination nodes are the same as those of path $p^r{}_L$.

Practically, in this search of the shortest path, we assign a weighted cost to branches that is proportional to the remaining wavelength to be stored. This is done to avoid concentrating assignment of paths to particular branches.

4 Simulation Results and Some Considerations

We made a prototype for the algorithm described in Section 3. In this section, we give the results of our simulation for some sample data, and mention some considerations for them.

Figure 5 is the sample network used in our simulation. It has 14 nodes and 21 branches. The capacities of all the branches are 5.

In this GMPLS network, optimal path design was conducted for each of the eight cases shown in Table 1. Out of all these cases, only in Case 1 was the design of 12 paths requested, with node A in Fig. 5 as the source node and node B as the termination node. For Cases 2 to 8, the designs of respectively 30, 50, 100, 500, 1000, 3000, and 10000 paths with two randomly selected nodes as the source node and termination nodes were requested. The line capacities were varied according to the number of paths requested in Cases 2 to 8.

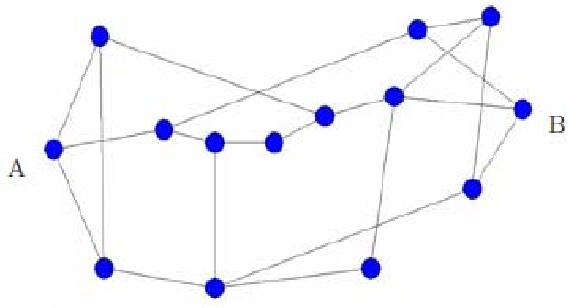

Fig.5 Sample network

Table 1 Setting of eight cases in simulation

	The number of requests for paths	The capacity of branches
Case1	12	5
Case2	30	15
Case3	50	25
Case4	100	50
Case5	500	250
Case6	1000	500
Case7	3000	1500
Case8	10000	5000

Table 2 gives the calculation results for the eight cases for the optimal path design method that is proposed in this paper. By performing a simulation, 10 different path-setting requests were created and tried for all the cases except for Case 1. Table 2 gives the average values of the 10 calculations for each case. The deviation of the solution in Table 2 is calculated by scaling the difference between the calculated value of the solution obtained using the optimal path design method proposed in this paper and the lower bound (i.e., (evaluated value of solution) - (lower bound)). The calculated value of the solution is determined using equation (6) in the primary problem (P2) that is used in the optimal path design method, while the evaluated value of the Lagrange solution is calculated using equation (11) in the Lagrangian relaxation problem (P3).

In the current simulation, the evaluated value of the solution agreed with the lower bound in the 1 trial for Case 1 and all of the 10 trials for Case 2, and it was confirmed that an optical solution was successfully outputted. In Cases 3, 4 and 5, an optimal solution was output successfully 6, 3, and 1 times out of 10 times, respectively. For the unsuccessful trials in Cases 3 to 5 and all the

Table 2 Result of eight cases

	Optimal solution (Achievement level)	Inaccuracy between output solution and lower bound	Average calculation time	Calculation time when the deviation become lower than 1% (Update frequency)
Case1	1/1 Achievement	0%	—	—
Case2	10/10 Achievement	0%	0.66 sec	0.02 sec (145 times)
Case3	6/10 Achievement	0.0326%	1.13 sec	0.05 sec (193 times)
Case4	3/10 Achievement	0.1860%	3.13 sec	0.32 sec (480 times)
Case5	1/10 Achievement	0.4313%	32.73 sec	5.63 sec (841 times)
Case6	Undetermined	0.6008%	126.64 sec	30.05 sec (1315 times)
Case7	Undetermined	0.6830%	1130.10 sec	341.41 sec (1600 times)
Case8	Undetermined	0.7688%	11195.42 sec	3366.80 sec (1578 times)

trials for Cases 6 to 8, the calculation was discontinued after attaining the preset number of iterations, even though there was still a difference between the evaluated value of the solution and the lower bound. In the current simulation, an update frequency of Lagrange multipliers in equation (27) of 5,000 was set as the condition for discontinuing the calculation. Since 5,000 times is insufficient to confirm a solution as being optimal, the entries in Table 2 say "Undetermined" .

First, we will confirm that the optimal path design method proposed in this paper functions effectively from the simulation results for the small-scale condition of Case 1. In Case 1, requests were specified for 12 paths from node A on the left side of the GMPLS network shown in Fig. 5 to node B on the right side. We solved the optimal path design problem under these assumptions and obtained the outputs shown in Fig. 6. The capacity of the five paths may be filled only when line *a* extends horizontally from node A to the right. However, by redirecting some of the paths, it was possible to free lines for the other branches. To meet the design request for 12 paths, the shortest distance of three hops was assigned to four paths, a distance of four hops was assigned to six paths, and a distance of five hops was assigned to two paths. If the shortest path to a line having a free capacity should be set for all path-setting requests, the shortest distance of three hops will be assigned to five paths and the distance of four hops will be assigned to seven paths in Case 1. In this case, however, three or more lines will be filled to their capacities. This confirms that the algorithm of the optimal path design method proposed in this paper is effective.

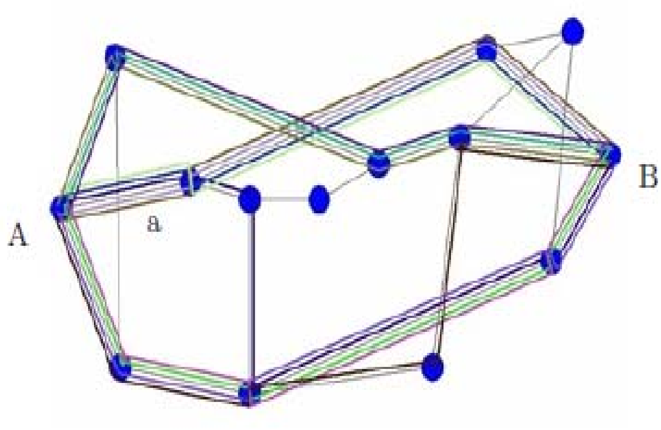

Fig. 6 Simulation results of with sample data

Figure 7 shows the results of the simulation for different assumptions, namely that branch "d" is unusable in situations such as when the line is broken. In this simulation, four requests take the shortest paths from node A to node B, four requests take four hops, two requests take five hops, and two requests take eight hops. Three branches, labeled "a", "b", and "c" in Fig. 7, have no spare capacity to be stored, but the other 18 branches have some spare capacity.

Next, we discuss the accuracy of the solution from the optimal path design method that indicates it differs from the optimal solution. As the third column in Table 2 shows, the deviation of the solution deteriorates as the number of path setting requests increases. However, in all cases the average deviation of the solutions is less than

1%. In particular, the deviation of all the solutions is below 1% in the trials of Case 1 and all of the 10 trials in Cases 2 to 7. In other words, although the proposed optimal path design only gives approximate solutions, these solutions are extremely close to the optimal solutions.

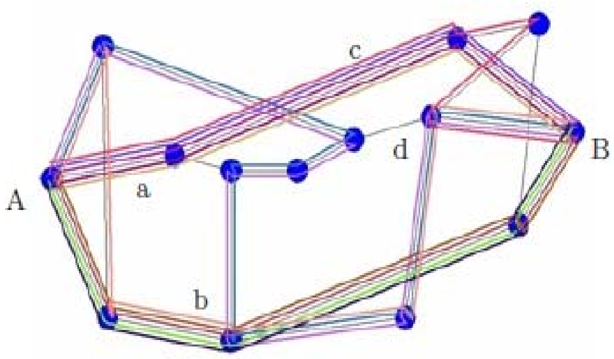

Fig. 7 Simulation results when branch "d" is removed

Figure 8 shows the time transition of the above deviations of the solution for Case 8. In a large-scale path design problem with many path requests, solutions cannot be expected to be optimal. In practice, the proposed optimal path design method by the Lagrangian relaxation method may not output optimal solutions because a heuristic algorithm is used to derive feasible solutions. In fact, the solution for Case 8 shown in Fig. 8 is not optimal since the time transition graph of the deviation is not zero. More accurately, the derived solution may be optimal but it cannot be guaranteed to be optimal since it exceeds the lower bound. However, this indicates that the proposed optimal path design method is capable of evaluating a lower bound quantitatively by utilizing the characteristics of the Lagrangian relaxation method. The accuracy of the solution from the optimal path design method can be presented quantitatively for a GMPLS network operator. As Table 2 shows, for Case 8 of Fig. 8, the calculation time was almost three hours. If the calculation should be discontinued after about one hour, the inaccuracy of solution will be about 1.5% relative to the lower bound. This implies that a further improvement of up to 1.5%can be expected. If the calculation of the optimal path design problem is continued in Case 8, the solution will improve about 90 minutes after the calculation has started calculation. Consequently, the final inaccuracy of solution will reach about 0.67% and a better solution will be obtained. In this example, the accuracy of the solution by the proposed optimal path design method could be improved by merely extending the calculation time. If the required improvement in the solution is known, we may recalculate the solution after adjusting several calculation parameters or use a different method other than the optimal path design method to obtain a solution. In Fig. 8, the deviation of the solution ceased improving once and then started to improve again when the update frequency of the Lagrange multipliers became about 2600. This occurred because the Lagrange multipliers λ_j in subproblem (P5) were updated using the results of equation (27) and a Lagrange solution could be obtained by using an update frequency of about 2600 times since the feasible solution became closer to the optimal solution. Therefore, this phenomenon depends on formulation by the proposed optimal path design method and the input data given in the case of Fig. 8, but it is independent of the characteristics of the Lagrangian relaxation method.

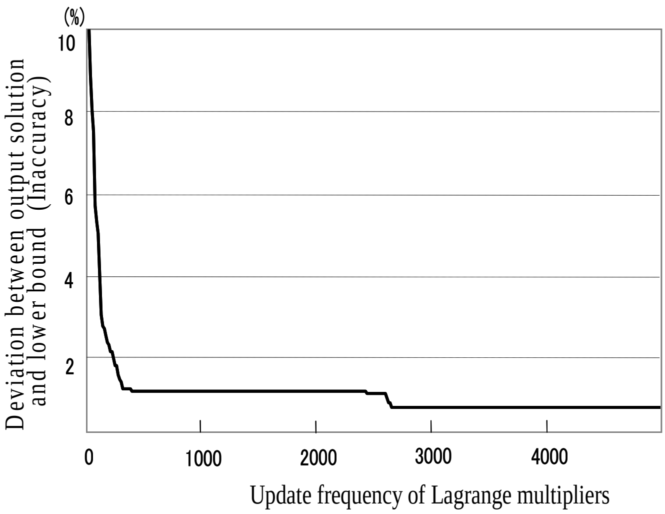

Fig. 8 Transition in between cost value for(P2) and low bound of (P6) in case 8

Finally, we discuss the calculation time of the optimal path design method. The fourth column of Table 2 gives the average calculation time for 10 trials for each case of the simulation. The computer used for this processing had a 3.2-GHz Intel Pentium 4 CPU and a memory of 1.0 GB. The calculation time for Case 1 was very short and is not given in Table 2 since we considered that the time taken to read and write to the hard disk was longer than the time required for the optimal path design method. In the current simulation, no optimal solution was output for almost all trials and thus the calculation processing was discontinued at the preset update frequency for the Lagrange multipliers (5000 times). Therefore, in order to discuss the calculation time of the optimal path design, the fifth column of Table 2 gives the calculation time and the update frequency of the Lagrange multipliers when the deviation of the solution became lower than 1%. Figure 9 shows a graph for the calculation time when the deviation was less than 1%. The vertical axis has a logarithmic scale for calculation time and the horizontal axis has a logarithmic scale for the number of path setting requests. As can be seen from Fig. 9, the proposed optimal path design method requires approximately O(n^2) iterations to obtain a solution whose deviation is guaranteed to be below 1%.

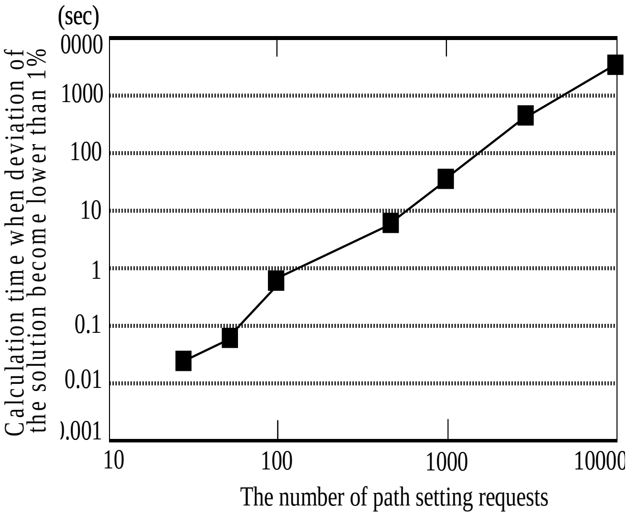

Fig. 9 Calculation time when deviation of the solution become lower than 1%

5 Conclusion

We presented a formulation of the path design for a GMPLS network and an algorithm that uses the Lagrangian relaxation method, which measures the deviation between a practical approximate solution and the optimal solution to enable us to evaluate the accuracy of the solution. We employ a heuristic algorithm to obtain a feasible solution, which is admittedly not the optimal solution. We can also obtain a lower bound for the problem. Therefore, we can evaluate the deviation by comparing the evaluated solution and the lower bound, even if the calculation stops before the optimal solution is obtained.

This indicates that a network operator can judge the accuracy of solutions then and use this knowledge to determine whether to reflect them as network paths.

The quantitative evaluation in the current simulation merely indicates the difference of the evaluated value from equation (6) of the optimal path design method in the primary problem (P2) from the value obtained using equation (11) of the Lagrangian relaxation method (P3). When presenting the evaluation result to a network operator, it is important to convert the evaluation value by the optimal paths design method to a cost value. We intend to investigate this aspect in the future.

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