ANT PATH OF TOPOLOGY FOR DYNAMIC ROUTING AND WAVELENGTH ASSIGNMENT IN WDM NETWORKS

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ABSTRACT

The typical constraints for wavelength allocation problem are the limited wavelength number on each link and the wavelength continuity constraint for all WDM networks. The interconnected multilayer-graph model (IMG) is used for the wavelength allocation. We consider that part of the nodes have wavelength conversion. For nodes without wavelength conversion capability, the wavelength continuity constraint is checked while establishing the light paths. The wavelength assignment algorithm assigns wavelengths to the primary and backup paths in order to share the resources between the current traffic requests and the already established requests. Thus, the proposed approach provides survivable routing in Wavelength Division Multiplexing (WDM) networks.

Keywords: Multilayer-graph model, interconnected multilayer-graph model (IMG), ACO algorithm

INTRODUCTION

In dynamic routing and wavelength assignment RWA [1], operation of connection management occurs in real-time and connecting and departing follow some probability distribution. Such a network must be very flexible in switching various wavelengths and light-paths between active source destination pairs. This flexibility in routing will make networks easy to configure and operate and also to improve the reliability of the network by providing easy set-up of alternate paths in case of node and link failures. There are two chief parameters of appraising dynamic RWA solutions: blocking probability and number of wavelengths used.

In a network where the traffic between the various source and destination nodes is known, one essentially needs to optimize light-path routing and wavelength selection in order to satisfy system constraints. The typical constraints are the limited wavelength number on each link and the wavelength continuity constraint for all Wavelength Division multiplexed (WDM) networks. The problem becomes more complex when considering the dynamic situation where new light-path requests are generated randomly between the various source-destination nodes and older light-paths randomly terminate and release their resources for reuse. Due to dynamic RWA being a NP-complete combinatorial problem, it is usually approximately separated into a routing and wavelength assignment sub-problem for reducing complexity [2, 3]. In these solutions, the
routing strategies usually are Shortest Routing and Least-loaded Routing, and the wavelength assignment strategies are First Fit, Least Influence, etc. But it is impossible to get overall optimization because of routing and wavelength assignment being an inseparable entity in fact. Instead of separated processing of the routing and wavelength assignment sub-problems, we consider the dynamic RWA problem as a whole. Thus, a new model called the multilayer-graph model [4] is put forward. Based on it, route selecting and wavelength assignment is completed simultaneously using the previous mentioned routing strategies for light-path requests. But it brings some problems: Most of the heuristic algorithms need global network status information and it must be refreshed frequently so that each node can maintain global network status information. Otherwise, the latest change of the network status cannot be reflected correctly. So the quantity of communication overhead cost and the source-node computation increase in large scale networks while dealing with more constraints.

In WDM networks without wavelength conversion, situations can occur where there still exist a significant total number of free channels, but one common free wavelength throughout a path cannot be found. Changing the wavelength along the lightpath can prevent this blocking phenomenon. The deployment of wavelength converters thus increases flexibility. However, it also adds high hardware costs. In Ref. [4], the authors only consider the case of with partial wavelength conversion. We extend the multilayer-graph approach in WDM networks without wavelength conversion.

Investigated the problem of Survivable Virtual Topology Routing [SVTR] under single fiber failure in WDM weighted mesh networks. They have proved necessary and sufficient conditions for the existence of survivable routes. Using that condition, they have proposed a polynomial algorithm that establishes survivable routes using a single wavelength. After creating this survivable ring virtual topology, they have assigned additional light paths using the available wavelengths at the various links to increase the one hop traffic mainly, giving priority on traffic and wavelength, respectively [5].

Have considered the problem of joint light path routing and capacity assignment for survivable IP-over- WDM networks. They have assumed that light path routing is determined in advance, and presented the light path routing has a significant impact on the spare capacity requirements. Finally they have developed new metrics for assessing the ”survivability” of a lightpath routing and joint lightpath routing and capacity assignment algorithms that use these metrics to reduce spare capacity requirements [11] proposed new distributed priority based routing algorithm which is intended for a variety of traffic classes. Their algorithm employs the concept of load balancing to establish the primary and backup light paths. Their algorithm calculates the cost metric on the basis of the load on the links. According to their algorithm the dynamic traffic can be classified into high and low priority. Here, the routing of high priority traffic is performed over the lightly loaded links, in such a manner that the links with lighter loads are chosen instead of links with heavier-loads whilst routing the primary and backup paths [13].
MULTILAYER-GRAPH MODEL IN WDM NETWORK WITHOUT WAVELENGTH CONVERSION

Based on the multilayer-graph model in Ref. [4], a light path must occupy the same wavelength on all links of the path used, a property known as the wavelength continuity constraint. Previous work has shown that wavelength conversion can considerably improve the performance in all optical networks. But it will cost much if all nodes in the WDM network have wavelength conversion. So we consider that part of the nodes have no wavelength conversion.

In this paper, we present an extended multilayer-graph model called the interconnected multilayer-graph model (IMG Define a network topology $G(N, E, W)$ for a given WDM network, where $N$ is the set of Optical Cross Connect (OXC)s without wavelength conversion capability, $E$ is the set of bidirectional links, and $W$ is the set of available wavelengths per fiber. Here, we assume that the set of wavelengths is identical on each fiber, i.e., $\{\lambda, \lambda_2, \ldots, \lambda_{|W|}\}$. The IMG($V, L$) is a directed graph, which can be obtained from a given network topology $G$ as follows. Each node $i \in N$ in $G$ is replicated $|W|$ times in IMG. These vertices are denoted by $v^1_i, v^2_i, \ldots, v^{|W|}_i \in V$.

If link $eij \in E$ connects node $i$ to $j$, where $i, j \in N$, then vertices $vw_i$ and $vw_j$ are connected by a couple of directed edges, $lw_i j, lw_i j \in L$ for all $w \in W$. Each node is simply connected on the same layer and vertical lines do not appear. Vertical arrows connect all duplicated nodes in all layers. The number of vertices in IMG is $|V| = |N| \times |W|$. Figure 1 shows an example of IMG, which is obtained from the physical network topology shown at the left side of the figure. Node $A$ is a source node. Node $H$ is a destination. The sub-graph induced by the vertex $vw s$ in the IMG is called the wavelength plane.

As shown in Fig. 1, by making use of the special structure of IMG, the RWA problem is reduced to the problem of finding a most optimized path with finite cost in the corresponding IMG.

ACO ALGORITHM FOR DYNAMIC RWA

There are two chief parameters in dynamic RWA solutions: blocking probability and number of wavelengths used. The objective we study is to minimize these parameters.

**Principle of ant colony optimization**

The basic idea of ant colony optimization is taken from the food searching behavior of real ants. When ants are on their way to search for food, they start from their nest and walk toward the food. When an ant reaches an intersection, it has to decide which branch to take next. While walking, ants deposit pheromone, which marks the route taken. The concentration of pheromone on a certain path is an indication of its usage. With time the concentration of pheromone decreases due to diffusion effects. This property is important because it is integrating dynamics into the path searching process. Figure 2 shows a scenario with two routes (solid lines) from the nest to the food place. At the intersection B, the first ant randomly selects the next branch, i.e., C
or BE. Since the route BE is shorter than BCE, the ants which take this path will reach the food place first. On their way back to the nest, the ants again have to select a path.

Fig. 1 Interconnected multilayer-graph model

After a short time the pheromone concentration on the shorter path BE will be higher than on the BCE, because the ants using the shorter path will increase the pheromone concentration faster. The shortest path BEF will thus be identified and eventually all ants will only use this one. If an obstacle O emerges on the path BGE unexpectedly in some time, ants will find another shorter way BDEF (if another shorter way, i.e., broken line in Fig. 2, existing or all ants will use the path BCHEF) based on the same strategy.
ACO heuristic on multilayer-graph model

Inspired by the behavior of real ants searching for food, the main idea is to utilize both local information (visibility) as well as information about good solutions obtained in the past (pheromone), when constructing new solutions.

Problem formulation and some relevant definition:

In this paper, we propose to study the following planning problem, given the physical topology of an optical network $G(N, E, W)$ together with link capacities. Given a set of aggregated traffic flows, the aim of the algorithm is to establish as many light-paths as possible for the set of aggregated traffic flows in the corresponding interconnected multilayer graph $IMG(V, L)$ in order to minimize the blocking rate. Given the number of all ants that are placed at the source node is $m$. Some relevant definitions are as follows:

1. Cost value $\rho_{ij}$ of using link $(i, j) \in L$ is given by

   $$\rho_{ij} = \begin{cases} 
   \omega \times L_{ij}, & \text{if link } (i, j) \text{ is free,} \\
   \infty & \text{otherwise,}
   \end{cases}$$

   where $L_{ij}$ is the actual length of the optical fiber corresponding to edge $(i, j)$ and $\omega$ is a constant that denotes the relative influence of $L_{ij}$;

2. Consider optical fiber $(I, J) \in E$ corresponding to edge $(i, j) \in L$ and given the number of light-paths in $(I, J)$ that has been occupied is $T$. We define the fiber-spare rate $\eta_{IJ}$ with regard to $(I, J)$ at time $t$ as follows:

   $$\eta_{IJ}(t) = \frac{|W| - T}{|W|},$$

Data structure

1. The information stored in each node $i$ (where we assume that the number of linked edges to node $i$ is $n$) is given by three matrices:
   - Cost table $C$ is a $N \times N$ sparse matrix in which the cost value of using each link is stored;
   - pheromone matrix $M(s, d)$ is a $N \times N$ sparse matrix corresponding to connect requests $(s, d)$. It is dynamically refreshed on algorithm progress;
   - matrix $O$ is a $|W| \times N$ sparse matrix which stores the status of light-paths, “1” denotes occupied, “0” denotes unoccupied.
(2) A iterate counter in source node limits the iteration number.

(3) The ant data packet format has the follows fields:

<table>
<thead>
<tr>
<th>H</th>
<th>S</th>
<th>SN</th>
<th>DN</th>
<th>PRI</th>
<th>MaxCN</th>
<th>FNN</th>
<th>Tab</th>
<th>Cost</th>
</tr>
</thead>
</table>

- **Head (H):** has four flags: setup, update, recall, affirm. It indicates what to do for every ant in one cycle.
- **Success (S):** success flag;
- **Source node (SN):** basic information about link request;
- **Destination node (DN):**
- **Priority value (PRI):**
- **MaxCycleNum (MaxCN):** max iterate number;
- **FindNextNum (FNN):** search counter, limits the search time;
- **Lists tabu [ ] (Tab):**
- **cost:** each ant keeping a tabu list of previously visited nodes as tabu [ ] which allows backtracking to avoid dead-ends and cycles — an approach adopted in the ACO algorithms in this paper. Sum of cost with regard to paths is saved in Cost [ ].

**Relevant main progress**

The relevant main progress consists of the following matrix handling strategies:

1. Initialize the strategy of the pheromone matrix: the pheromone information value is stored in the pheromone matrix, which is a $N \times N$ symmetric sparse matrix $M$ in the node. The initial information value is defined as:

   \[
   \phi_{ij}^0 = \lambda \eta_{ij},
   \]

   where $\lambda$ is a constant to counterpoise the cost of reducing local cost and balancing fiber-blocking. To alleviate the early stagnation of the search that makes further tour improvements impossible, we explicitly limit information value in $[\phi_{\text{min}}, \phi_{\text{max}}]$, which is similar to idea of the Max_Min Ant System (MMAS) \[8\]. The limits are chosen depending on the average arc length \[9\]. So the actual initial information value corresponding to edge $(i, j)$ can thus be represented as:

   \[
   \phi_{ij}^0 = \begin{cases} 
   \phi_{\text{min}}, & \phi_{ij}^0 < \phi_{\text{min}}, \\
   \phi_{ij}^0, & \phi_{\text{min}} \leq \phi_{ij}^0 \leq \phi_{\text{max}}, \\
   \phi_{\text{max}}, & \phi_{ij}^0 > \phi_{\text{max}}.
   \end{cases}
   \]

2. Select the strategy for ant $k$ at node $i$ to choose next node $j$ at time $t$ based on pheromone matrix $M$: as a load balancing strategy, the algorithm will prefer nodes with a higher fiber-spare rate as the next node to those with a lower one, which can dramatically reduce blocking probability for dynamic business. The probability $P_k(\phi_{ij}(t))$ for ant $k$ at node $i$ to select next node $j$ at time $t$ is defined as follow
\[
\begin{align*}
\Delta \phi_{ij}^k &= \begin{cases} 
\frac{\text{const}}{\varrho_{ij}} + \frac{\chi \eta_{IJ} (t+1)}{\text{CostSum}_k} & \text{if ant } k \text{ passed } (i, j) \text{ and } \sum_{(i,j) \in \text{PASSED}_k} \varrho_{ij} < \infty, \\
0, & \text{otherwise.}
\end{cases}
\end{align*}
\]

where \( \phi_{ij}^k (t) \) is the information value in pheromone matrix \( M \) corresponding to edge \((i, j)\) and is the information about good solutions obtained in the past (pheromone);

\[
\delta_{ij}(t) = \frac{\text{const}}{\varrho_{ij}} + \chi \eta_{IJ} (t + 1)
\]

is the local heuristic information (visibility), and is concerned with cost \( \varrho_{ij} \) and fiber-spare rate \( \eta_{IJ} \); \( \alpha \) and \( \beta \) are constants and, respectively, denote relative of the past (pheromone) and the local heuristic information criteria. \( Ak \) is a set of next nodes that ant \( k \) will possible select. Each ant keeps a tabu list of previously visited nodes as tabu [ ]. If allows backtracking to avoid dead-ends and cycles—an approach adopted in the ACO algorithms in this paper;

\[
\forall j \in A_k^i, \quad \text{if } P_{ij}^k (t) = 0,]
\]

ant \( k \) will randomly select next node \( j \) \((j \in Ak \) \); The constant \( \text{Cycleini} \) is the initial cycle number; the parameter \( \text{MainCycle} \) denotes the main cycle number which program has processed. When \( \text{MainCycle} < \text{Cycleini} \), ant \( k \) will randomly select next node \( j \) \((j \in Ak \) \) to expand its searching area in IMG.

3) Update the strategy of the pheromone matrix: after all ants have found a path from source node to destination node i.e., one cycle has finished, the information value corresponding to each edge \((i, j)\), with \((i, j) \in L\), must be updated.
Fig. 3 ACO flowchart
The information value in the pheromone matrix corresponding to each edge \((i, j)\) after updating can thus be represented as:

\[
\varphi_{ij}(t + 1) = \theta \varphi_{ij}(t) + \sum_{k=1}^{m} \Delta \varphi_{ij}^{k},
\]

where the parameter \(\theta(0 < \theta < 1)\) reduces the current information value to enhance the relative importance of the local heuristic information. The value \(1 - \theta\) is the reduce rate.

(4) Repeat the searching progress when all ants are replaced at the source node: When all ants have concentrated on one path eventually or MainCycle exceeded the maximum that we set previously to limit executing time to a reasonable range, the circulation will be stopped. In the former case, that path is just we want. If MainCycle exceeds the maximum and all ants do not use one route, the route with the largest information value within all routes found with the limited sum of cost will be taken. Otherwise, the trial result will be set to failure. For the demonstration of the validity of convergence of ACO based algorithms we refer to Dorigo [10]. A flowchart for the ACO algorithm applied in this paper is presented in Fig. 3.
SIMULATION RESULTS AND ANALYSIS

For the purpose of performance evaluation, network blocking is here the primary focus. Blocking probability measurements are based on loading the network to full capacity. In all tests, the traffic for a source-destination pair arrives according to a Poisson process with rate $\lambda$. A connection request will be rejected as soon as connection setting up ends in failure, there is no waiting list. Testing was conducted on a 22-node, 31-link network, in Fig. 4, with a similar physical topology to CERNET network in East (North) China, which is a mixed structure of stars and rings. Each edge in the network has a capacity of 16 wavelengths for all tests and the cost of using every edge is explicitly given in Fig. 4.

Mokhtar and Azizoglu present several heuristic RWA algorithms in [3]. They achieve the best results through an exhaustive search over all wavelengths for the shortest available path from source to destination. Their exhaustive search provided lower blocking than methods employing static routing, and provides a benchmark for the ACO algorithm presented in this paper.

After several previous trials, we got best performance using parameters values as follows: $I_{const} = 50; \phi_{min} = 4.9; \phi_{max} = 20.2; \alpha = \beta = 0.9; \theta = 0.85; \chi = 10; \varepsilon = 0.25; \text{CycleIni}=10$. Using 64 ants and a maximum of MainCycle set to 200, the ACO algorithm outperforms the shortest available path at most traffic load but in lighter-than-ordinarily load case, as shown in Fig. 5. These results seem to indicate that the ACO algorithm has some executing uncertainty. In the no
wavelength conversion case, when the network load is lighter-than-ordinarily, network blocking is mainly wavelength-blocking, i.e., there are no light-paths that can satisfy the wavelength continuity constraint even when each physical fiber has spare paths. In this case, there is a slight possibility that the algorithm missed some existing light-paths by reason of ACO’s uncertainty in spite of the wavelength conversion capability. When the network load increases, network blocking is mainly capacity-blocking. In this case, the ACO algorithm can provide the best results by using optimization techniques.

Although, several parameters are concerned with algorithm performance, we focus on the number of ants. As shown in Fig. 6, increasing the number of ants per connection request increases the likelihood that more paths are explored and better solutions found. But, performance will only improve up to a certain number of ants (< 80 in Fig. 6) and significant processing is required with a large number of ants. However, this increased processing load is easily distributed.

**CONCLUSIONS**

In this paper, we presented a new distributed ACO heuristic dynamic RWA approach for WDM networks without wavelength conversion and solved the dynamic RWA problem based on an IMG model successfully. This ACO method is parallel, distributed, and robust. Compared with other RWA methods [2–4], we can get global network optimization easily and reduce communication overhead cost of networks. Simulation showed its ability to outperform the best performing methods by using large numbers of ants. Also in the simulating process, we found some problems, such as sometimes the speed of convergence is slow and there is a tendency that the ACO algorithm matures early. We are working further on the implementation to improve the algorithm in executing time and stability. Additionally, analysis of the maintenance of the
pheromone concentration is needed. There are different ways to manipulate the pheromone concentration on the edges, which influence the performance of the routing algorithm.

REFERENCES