An Ant-based Approach for Dynamic RWA in Optical WDM Networks

Son Hong Ngo[1], Xiaohong Jiang[1] and Susumu Horiguchi[1,2]
1. Graduate School of Information Science, Japan Advanced Institute of Science and Technology, Japan
2. School of Information Sciences, Tohoku University, Sendai, Japan
{sonhong, jiang, hori}@jaist.ac.jp

Abstract - In this paper, we propose a new ant-based algorithm for the dynamic routing and wavelength assignment (RWA) problem in optical WDM networks under the wavelength continuity constraint. Unlike conventional approaches, which usually require centralized global network information, our new RWA algorithm constructs the routing solution in a distributed manner by means of cooperative ants. To facilitate the ants' foraging task, we adopt in our algorithm a probabilistic routing table structure for route selection. The new algorithm is highly adaptive in that it always keeps a suitable number of ants in the network to cooperatively explore the network states and continuously update the routing tables, so that the route for a connection request can be determined promptly by the current states of routing tables with only a small setup delay. Some new schemes for path scoring and path searching are also proposed to enhance the performance of our ant-based algorithm. Extensive simulation results upon three typical network topologies indicate that the proposed algorithm has a very good adaptability to traffic variations and it outperforms both the fixed routing algorithm and the promising fixed-alternate routing algorithm in terms of blocking probability. The ability to guarantee both a low blocking probability and a small setup delay makes the new ant-based routing algorithm very attractive for both the optical circuit switching networks and future optical burst switching works.

Keywords: Ant-based routing, Routing and wavelength assignment (RWA), WDM networks.

I. INTRODUCTION

Because of their huge bandwidth capacity, all-optical Wavelength Division Multiplexing (WDM) networks hold great promise to serve as the backbone for future wide area networks [1]. It is envisioned that the next generation WDM networks will work in a hybrid mode, in which Optical Circuit Switching (OCS) and Optical Burst Switching (OBS) serve as two distinct layers that co-exist in the network and complement each other [2]-[3]. The capacity in the OCS layer is designed for providing synchronous services, such as multimedia services with requests issued in advance. On the other hand, the capacity in the OBS layer is for satisfying immediate and asynchronous bandwidth requests with rapid traffic variation and bursty demands which might cause inefficiency if they are provisioned in the OCS layer. To support both the OCS and OBS efficiently in such hybrid optical networks, a lightpath must be dynamically established with a low blocking probability and a small setup delay at the time a

connection request arrives. For lightpath establishment, we need to solve the so-called routing and wavelength assignment (RWA) problem.

The RWA problem is one of the most important issues in WDM networks; it involves in determining the routes and wavelengths to be used to establish lightpaths for connection requests. RWA problems can be generally classified into two types: *static* and *dynamic.* In a static RWA problem, network topology and connection-establishing requirements are given in advance, and the problem is to find a solution that satisfies certain optimizing conditions, such as minimizing the number of wavelengths or maximizing the total number of lightpaths that can be established. Dynamic RWA problems involve the on-line establishment of lightpaths for connection requests that arrive dynamically. The static RWA problem is proved as a NP-hard problem [4,5]. The dynamic RWA problem is much more difficult to solve, therefore heuristics algorithms are usually employed to solve it.

A lightpath must use the same wavelength on all of its links if there is no wavelength converter at intermediate nodes; this is known as the wavelength continuity constraint. In this paper, we focus on the dynamic RWA problem under the wavelength continuity constraint. Many approaches have been proposed for solving the dynamic RWA problem [6]-[10], and these approaches can be generally classified into three basic classes: *fixed routing*, *fixed-alternate routing* and *adaptive routing*. In the fixed routing approach, a fixed shortest path is statically computed for a node pair. Whenever a request arrives between the node pair, the fixed path is always attempted for wavelength assignment. This method is simple but it tends to introduce a high blocking probability. In fixed-alternate routing, a node pair has a set of pre-computed shortest paths and all of them will be attempted for lightpath establishment upon the arrival of a connection request. In the adaptive routing approach, the path for a connection request is computed upon its arrival based on the current network state, thus it provides the lowest blocking probability [4,6]. However, adaptive routing usually requires higher computation complexity and thus introduces a longer setup delay than fixed-alternate routing. Moreover, adaptive routing requires higher control overhead, including special support from control protocols to keep track of the up-to-date global network state, which makes it practically infeasible for large and highly dynamic networks. Fixed-alternate routing is now considered as a very promising routing algorithm, because it significantly reduces blocking probability in comparison with the fixed routing algorithm and it achieves a good trade-off between performance and control overhead [7]. Actually, a fixed-alternate routing algorithm with a small number of alternate routes asymptotically approaches the performance of an adaptive routing algorithm in terms of blocking probability [8].

In this work, we investigate an ant-based approach for dynamic RWA problem based on the idea of Ant-Colony Optimisation [11,12]. Inspired by the behavior of natural ant systems, a new class of ant-based algorithms for routing in communication networks are currently being developed. Previous work

has shown the potential success of ant-based routing for both packet switching networks (e.g. AntNet [13]) and circuit switching telephone networks (e.g. ABC [14]). However, few results are available for applying the ant-based approach to the challenging RWA problem (especially the dynamic RWA problem) in WDM networks. This paper aims to develop a new dynamic RWA algorithm using an ant-based approach. The main contributions of our work are:

- We first introduce an ant-based dynamic routing algorithm for WDM networks under the wavelength continuity constraint. The path for a connection request is determined promptly based on current states of routing tables, which are continuously updated with an adjustable number of cooperative ants.
- We extend the conventional path-scoring methods by using both congestion information and the length difference between the current path and the shortest path to ~~a~~ more efficiently update the routing table. We also provide a new path-searching scheme to enhance the performance of our ant-based algorithm.

Our ant-based algorithm does not require global information of network states for route selection as do other adaptive RWA routing algorithms, and it enables the path for a connection request to be determined promptly by simply using the routing table lookup with a small setup time. An extensive simulation study shows that our proposed ant-based RWA algorithm performs better than the promising fixed-alternated routing algorithm in terms of blocking probability. These attractive characteristics make the new ant-based dynamic RWA algorithm a promising candidate for the next generation of optical WDM networks.

The rest of this paper is organized as follows: In section II, we discuss related work. Section III presents our ant-based algorithm for solving the dynamic RWA problem in WDM networks under the wavelength continuity constraint. Section IV provides simulation results and analysis. We conclude this paper with a discussion in Section V.

II. RELATED WORKS

Schoonderwoerd et al. proposed an ant-based routing algorithm for circuit switching telephone networks in [14]. In this algorithm, an ant-based agent modifies the routing policy at every node by deposing a pheromone trail on its routing table; the agents' goal is to build the routing tables and to adapt them to the load changes at run time so that the accepting ratio of coming calls is maximized. Bonabeau et al. [15] improved the performance of Schoonderwoerd's algorithm based on the principle of dynamic programming. However, Bonabeau's algorithm cannot be directly applied to WDM networks because of the wavelength continuity constraint. Our approach builds upon the above

algorithms while taking into account the wavelength assignment with wavelength continuity constraint in WDM networks.

Some ACO-based algorithms have also been proposed for solving RWA algorithms in WDM networks. In the static RWA scenario, Varela et al. [16] applied ACO to minimize the total number of wavelengths in the case of RWA with wavelength conversion. Varela's algorithm can achieve a result that is comparable to conventional heuristics, but it requires a much longer computational time. Gonzalez et al. [17] proposed a similar approach for lightpath routing and wavelength assignment algorithm by means of ACO in the case of RWA with a wavelength continuity constraint. It is notable, however, that neither of the above two algorithms can be applied directly to the dynamic RWA problem.

Garlick et al. [18] proposed, for the first time, an algorithm for solving the dynamic RWA problem via ACO. Garlick's algorithm works as follows: when a connection request arrives at a node, a number of ants are launched from the source to the destination to search for paths. An ant reports a path between the source and destination once it reaches the destination. Each reported path is scored based on its length and congestion information. After all the ants reach the destination, a best path is selected from all the reported paths to establish the connection request. In comparison with conventional approaches, this algorithm can achieve good performance in terms of blocking probability; however, a connection request will suffer from a high setup delay due to the need to wait for all ants to complete their search. Basically, the ants launching from one node do not cooperate with the ants from other nodes.

III. ANT-BASED ALGORITHM FOR DYNAMIC RWA PROBLEM

In this section, we present our ant-based dynamic RWA algorithm in optical WDM networks with irregular topology. Our algorithm differs from Garlick's algorithm [18] in that cooperative ants are used to continuously update the routing table on each node such that the current network state can be reflected in the routing tables. By this way, the path of a connection request can be determined promptly on its arrival while a low blocking probability is guaranteed. Unlike the routing in circuit switching telephone networks [14], we need to consider the wavelength conversion capability while applying the ant-based algorithm to the RWA problem in WDM networks. In our algorithm, the ants will take into account the wavelength continuity information during the routing table updating process.

The ants used in our algorithm are transported in a separate control plane. We suppose that this control plane of a WDM optical network is carried out in a packet switching network that has the same topology as the optical network. This assumption is based on the fact that control data can be transported in several ways, such as through an out-of-band electronic network or through a dedicated wavelength in the optical domain [1].

In the following section, we present in detail the new ant-based algorithm for solving the dynamic RWA problem.

A. Network Model and Routing Table Structure

We assume that the lightpaths are undirected and symmetric. This assumption assures that the same route and wavelength are assigned for both directions with the same cost. We also focus on the wavelength continuity constraint in which a same wavelength must be used for all the links of a lightpath. With the above assumptions, a network can be represented by an undirected graph with N nodes and some bi-directional links. Each link has the same capacity of W wavelengths and no nodes have wavelength conversion capability (wavelength continuity constraint).

To support dynamic route selection, a node i with k_i neighbors has a routing table $R_i = [\ r^i_{n,d}\ ]_{ki,\ N\text{-}1}$ with N–1 rows and k_i columns. Each row corresponds to a destination node and each column corresponds to a neighbor node. Like the routing table structure proposed by the ABC algorithm [14], the value $r^i_{n,d}$ expresses the goodness of choosing n as the next hop in establishing a lightpath. It is also used as the selection probability of neighbor node n when an ant moves toward its destination node d. An example of the routing table is shown in Fig.1. When a connection request occurs between the source node 3 and the destination node 0, node 1 will be selected as the next hop because $r^0_{1,0} > r^0_{4,0} > r^0_{5,0}$

For each destination, the sum of all neighbors' selectoin probabilities must be 1 to satisfy the normalized condition:

$$\sum_{n \in Nb_k} r^i_{n,d} = 1, \qquad d \in [1, N], \qquad Nb_k = \{neighbors(k)\} \tag{1}$$

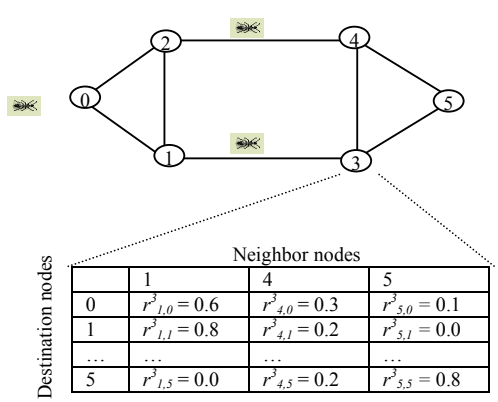


Fig. 1 A network and its routing table architecture on node 3.

B. Ant's Foraging and Routing Table Updating

The main idea of our ant-based algorithm is adopting the cooperative behavior of ant colonies to adaptively discover a route for lightpath establishment. To achieve that goal, ants are launched from

each node with a given probability ρ to a randomly selected destination every T time units. Here ρ and T are design parameters. Each ant is considered as a mobile agent: it collects data on its trip, performs routing table updating on visited nodes and continues to move forward as illustrated in Fig. 2.

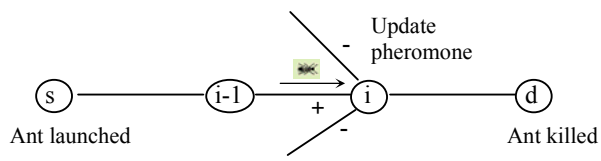


Fig. 2 Ant's moving and updating tasks.

1. Data Collected by Ants

~~a~~Ants collect two kinds of data along their trips: path length and congestion information. Each ant carries a binary mask M_{ant} that indicates the available wavelengths on its path; this mask has W bits corresponds to the number of wavelengths. The bit value 1 corresponds to a free wavelength while the bit value 0 corresponds to a busy wavelength. Under the wavelength continuity constraint, a wavelength can be assigned only if it is free on all links of the path. Thus, at each node, the wavelength mask is updated as follow:

$$M_{ant} = M_{ant} \text{ AND } M_{link} \tag{2}$$

Where: M_{ant} is the actual mask carried by the ant

M_{link} is the mask for available wavelengths on next selected link

2. Routing Table Updating

Whenever an ant visits a node, it updates the routing table (pheromone updating). Suppose an ant moves from the source node s to destination node d following the route ($s, \ldots, i$-1, $i, \ldots, d$), it will update the entry corresponding to the source node s in the routing table of node i as follows: the probability of selecting neighbor i-1 is increased while the probabilities of selecting other neighbors are decreased (Fig. 2). More formally, suppose that an ant visits node i at time t, so the values for routing entry in time t+1 are determined by the following formula (remember that the sum of selecting probabilities for all neighbors is always 1):

$$r^{i}_{i-1,s}(t+1) = \frac{r^{i}_{i-1,s}(t) + \delta r}{1+\delta r} \tag{3}$$

$$r^{i}_{n,s}(t+1) = \frac{r^{i}_{n,s}(t)}{1+\delta r}, n \neq i-1 \tag{4}$$

Here, δr is the reinforcement parameter and is derived from the data collected by the ant. In the basic ant-based routing algorithm for WDM networks [19], this parameter (amount of trailing pheromone) is

computed by the following principle: the amount of trailing pheromone decreases with increasing path length and increases with an increased number of available wavelengths.

Let δl be the amount of pheromone corresponding to the path length and δw be the amount of pheromone corresponding to the percent of free wavelengths of the path that the ant has moved along. We introduce here a scalar parameter α such that we can adjust the weight between δl and δw in δr as follows:

$$\delta r = \alpha \cdot \delta l + (1-\alpha) \cdot \delta w, \qquad 0 \le \alpha \le 1 \tag{5}$$

The factor δl is derived from the length of the path that the ant has moved along. The shorter the path length, the bigger the δl value, and vice versa. Note that the length l of a path between a source-destination node pair is always greater than or equal to the length of the shortest path between the source and the destination (denoted by l_{min} hereafter), and as a reinforcement parameter, δl must be small and $0<\delta l<1$ [14]. Thus, we compute δl as follows:

$$\delta l = e^{-\beta \cdot \Delta l}, \qquad \Delta l = l - l_{\min} \tag{6}$$

where β is a control parameter. Since the absolute value of path length varies significantly in a large network, using the length difference instead of the absolute length in determining the reinforcement parameter δl enables the pheromone updating process for all node pairs to be controlled by the same parameter β.

The factor δw is derived from the percent of free wavelengths in the path that the ant has moved along. The path with more free wavelengths has a larger value of δw. Similar to δl, δw must be a small value and $0<\delta w<1$. We can compute δw as follows:

$$\delta w = e^{\gamma \cdot w} - 1 \tag{7}$$

where γ is another control parameter. Here α, β and γ are design parameters and can be adjusted to get the best system performance.

3. Ant Movement

When an ant moves from a source to a destination, its next hop is determined stochastically: a neighbor is selected according to its selection probabilities in the routing table. This is the basic principle of ant colony optimization [11,12]. As a result, an ant colony tends to discover the better path between a node pair in terms of path length and the degree of congestion along this path.

In our algorithm, an ant is killed when it reaches its destination node or when it cannot find a path with a free wavelength to which to move. An ant is also killed if its lifetime exceeds a predefined value TTL (Time-to-Live), or if it detects a loop on its path (by searching the visited nodes in the ant's stack).

Ant-based algorithms usually suffer from *stagnation*, in which an optimal path is found by ants so the pheromone for this path is recursively increased [20]. In this case, too many ants concentrate on this

optimal path, which prevents them from discovering other, better paths when the network state changes. To avoid this "frozen" situation, a random scheme with a "exploration" factor P_{noise} is introduced: at each node; the ant selects its next hop randomly with an exploiting probability P_{noise} and selects its next hop according to the routing table with probability 1-P_{noise}. The using of P_{noise} allows ants to keep exploring for a better solution to a lightpath request.

4. Smart Updating

As described in [15], agents supplemented with dynamic programming capacity, or smart agents, are efficient in improving the performance of ant-based routing systems. With the idea of smart agents, the pheromone updating affects not only the entry corresponding to the source node, but also all the entries corresponding to previous nodes the ant has visited. In order to facilitate the smart updating, an ant must push into its stack the node identification and a binary mask that determines the states of wavelengths on all the links it has traversed. Under the wavelength continuity constraint, this wavelength mask is determined in a same way as described in section III.B.1. This stack also serves for loop detection and backtracking, to ensure that ants will not move forever on the network.

C. Selection of Path and Wavelength

With support from the routing table and the ant's foraging, path selection can be performed in a straightforward manner as described in our previous work on ant-based algorithms [20]: when a connection request arrives at the source node, the next hop will be determined by the node with the highest selection probability among all its neighboring entries. The visited nodes will never be selected as the next hop. This principle is applied from the source node to the destination node. We call this the *First-Highest* scheme. With this scheme, the route is already determined upon the arrival of a connection request.

After determining the route for a connection request, any wavelength assignment scheme can be applied [9]. Our work in this paper does not focus on ant-based wavelength assignment heuristics, so we use First-Fit [9]- a simple yet efficient heuristic for wavelength assignment. In the First Fit heuristic, all wavelengths are considered and the first available one is selected.

As explained in [19], ant-based algorithms adopting the First-Highest scheme have a *stagnation* state problem. When the network state changes, e.g., when a lightpath is established or released, ants may not be able to quickly find a better path for a new request. This phenomenon greatly affects the performance of ant-based dynamic RWA algorithms with a wavelength continuity constraint, since the state change of a wavelength on one link may affect the overall RWA solution. Here, we introduce here a new path selection scheme, called the *Second-Highest* scheme, to enlarge the search space for RWA solution based on the ants' searching. In the *Second-Highest* scheme, we will try the second route as follows if there is no free wavelength available on the first route, as obtained by the First-Highest

scheme: at the source node, the next hop is determined by the node with the second highest selection probability, after this hop, the First-Highest scheme is used again until the destination node is reached. The wavelength assignment for the second route is also based on the First-Fit heuristic.

The pseudo-code of our ant-based RWA algorithm with the Second-Highest scheme and First-Fit wavelength assignment is summarized as follows:

```
{Ant generation}
Do
    For each node in network
        Select a random destination;
        Launch ants to this destination with a probability ρ
    End for
    Increase time by a time-step for ants' generation
Until (end of simulation)
{Ant foraging}
For each ant from source s to destination d do (in parallel)
    While current node i <> d and TTL > 0
        Smart-update routing table elements
        Push trip's state into stack
        If  (found a next hop)
            Move to next hop and decrease TTL
        Else
            Kill ant
        End if
    End while
End for
{Routing and Wavelength Assignment}
For each connection request do (in parallel)
    Select a path based on first-highest-probability-lookup
    Select the first available wavelength on path
    If (found)
        Setup a lightpath
    Else
        Select another path based on second highest probability
        Select the first available wavelength on path
        If (found)
            Setup a lightpath
        Else
            Consider a blocking case
        End if
    End if
End for
```

IV. SIMULATION RESULTS AND ANALYSIS

An extensive simulation study based on the ns-2 network simulator [21] has been performed to verify our new ant-based dynamic RWA algorithm for WDM networks with wavelength continuity constraint. In the simulation, each ant is considered as a packet and it is simulated based on the packet-switched

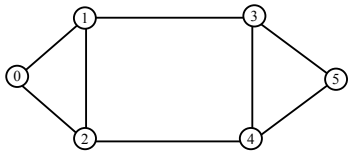
feature of ns-2. As the size of each ant is relatively small, so its delay is negligible. A circuit-switched routing module is also added into ns-2 to simulate our RWA algorithm.

A. Experimental Settings

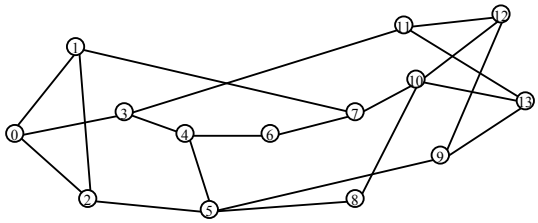
This section briefly introduces the network topologies and traffic pattern used in our simulation.

1. Network Topology

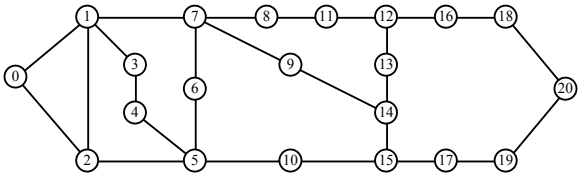
Three typical network topologies (see Fig.3) are adopted in our simulation. The main properties of each network topology are characterized by three parameters (*h, d, N*) that indicate respectively the average shortest path, the variance of the average shortest path, and the number of nodes. Basically, the difficulty of the routing problem increases with the value of these numbers [13].



a) SimpleNet (1.5, 0.4, 6) with 8 links.



b) NSFNet backbone (2.2, 0.6, 14) with 21 links.



c) ARPA-2 backbone (3.5, 2.7, 21) with 26 links.

Fig. 3. Network topologies used in simulation.

2. Traffic Pattern

For our simulation we adopted the general dynamic traffic model widely used in the performance analysis of data communication networks [22]. For spatial distribution, arriving sessions are distributed randomly over the network. For temporal distribution, connection requests arrive at each node according to a Poisson process with an arrival rate λ (call/s). The session holding time is exponentially distributed with mean μ (the mean session holding time is μ seconds). If there are T sessions over all of

the network, then the total network load is measured by $T \cdot \lambda \cdot \mu$ (Erlangs). In our experiments, we keep the parameters T and μ as constants and modify parameter λ to have different traffic loads.

B. Algorithms Used for Comparison

The routing algorithms used for comparison are the fixed routing algorithm and the fixed–alternate routing algorithm.

Fixed routing [9]**:** The Dijkstra or Bellman-Ford algorithm is used off-line to compute the shortest path for each source-destination node pair. When a connection request arrives at a source node, the fixed shortest path between the source node and its destination is taken to establish the lightpath. An implementation of the shortest-path algorithm is available in ns-2 [21].

Fixed-alternate routing [7]: Each node has a routing table that contains a list of fixed routes to each destination node. When a connection request arrives, the source node attempts routes in sequence until a valid wavelength is found for lightpath establishment. Otherwise, the request is blocked. Empirical results indicate that the performance of fixed-alternate routing with a small number of alternate routes asymptotically approaches that of adaptive routing in reduced blocking probability. Two alternate routes are tested in our experiments: the first route is the shortest path; the alternate route is the shortest among all other paths. An example of the implementation of fixed-alternate routing is shown in [23].

All the routing algorithms in this paper use the First-Fit heuristic for wavelength assignment.

C. Parameters Setting and Tuning

The main parameters used in our simulations are summarized in Table 1. The time step for ant generation is set as t=1ms, and the delay for each link is assumed to be 10ms. Two values for the number of wavelengths W per link, 8 and 16, are adopted in the simulation. For each case, there ~~in~~ is a total T sessions with the session holding time being set as μ = 5s. The arrival rate λ is modified to have different load values. The network load is selected so that the Fixed-Alternate algorithm can achieve a practical blocking probability (about 5%). The number of ants is mainly controlled by the ant's launching probability $\rho \in [0,1]$, and the parameter ρ is adjusted to achieve the lowest blocking probability. To get a stable result, the each experiment is run in 1000s and it is repeated five times to get the average value of blocking probability.

Table 1. Parameters value used in simulations

Network	(W_1, T_1)	(W_2, T_2)	λ	α, β, γ	P_{noise}
SimpleNet	(8, 60)	(16, 120)	0.08-0.16	0.8, 1.75, 0.2	0.05
NSFNet	(8, 100)	(16, 200)	0.05-0.07	0.8, 1.75, 0.2	0.06
ARPA-2	(8, 75)	(16, 150)	0.06-0.14	0.6, 1.75, 0.2	0.06

For each network topology, we use the same set of parameters (α, β, γ) for pheromone control, as determined from our previous simulation results. We found this set of empirical parameters is usually good enough for us to achieve a satisfactory performance for different network topologies. However,

determining an optimum set of parameters (α, β, γ) for an ant-based algorithm to achieve the best performance remains an open problem, which deserves further research efforts.

In order to get the routing tables into a ready state, the algorithm is first allocated an initial pre-defined running time with a fixed number of ants and without traffic load, in which the routing tables are initialised with equal probability for each neighbor node. During this initial period, only path length information is taken into account when ants update the routing tables. At the end of the initial period, our simulation results show that the routing tables indicate the shortest path between each node pair. This result has also been demonstrated in previous work [14]. After the initialisation period, the traffic is then loaded into the network. We first keep $\rho = 0$, so the performance of ant-based routing is the same as the fixed routing algorithm because there is no ants available to explore the network state. We then tune the number of ants by increasing ρ to get a lower blocking probability. Fig. 4 illustrates the relation between the blocking probability and the ants' launching probability in the SimpleNet topology.

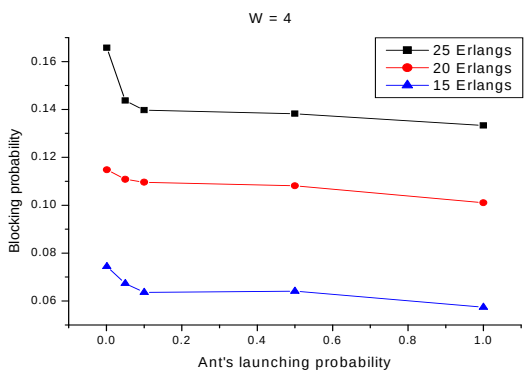


Fig. 4. Blocking probability vs. ρ on SimpleNet.

We can observe from Fig.4 that the blocking probability decreased significantly when ρ was increased from 0 to 0.1. However, when we increase the value of ρ further, from 0.1 to 0.9, to have an increased numbers of ants exploring the network, we are not able to significantly reduce the blocking probability any further. In fact, too many ants in the network ($\rho \approx 1$) will cause a high control overhead. It is interesting to note in Fig.4 that a good performance in terms of low blocking probability can be obtained within a large range of ρ. Thus, our ant-based algorithm has good robustness to the variation of parameter ρ.

D. Results and Analysis

Extensive simulation has been conducted upon the three networks shown in Fig.3, and the corresponding comparison results among Shortest Path (SP), Fixed-Alternate (FA) and our Ant-based (AB) routing algorithms are summarized in Fig.5.

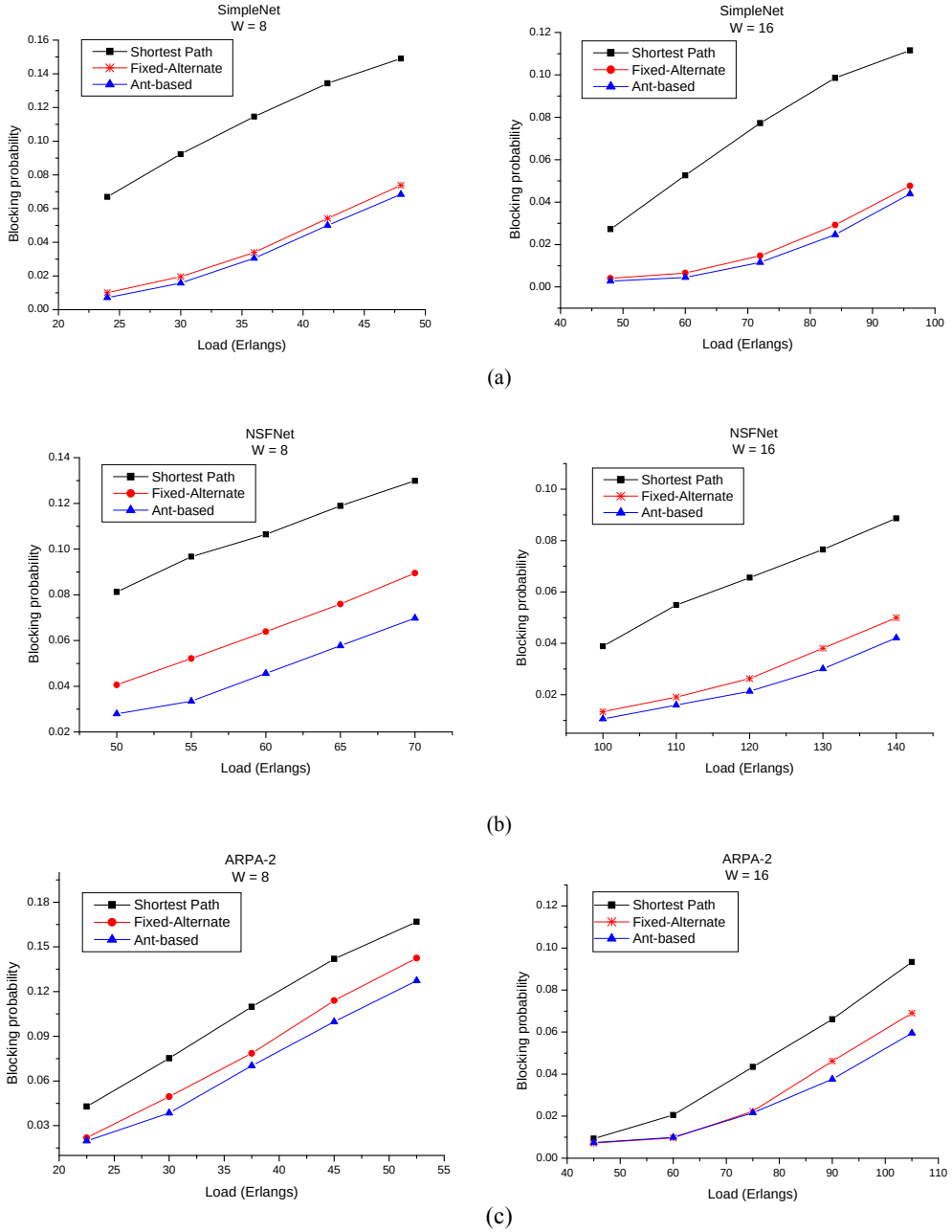


Fig. 5. Comparisons between new ant-based algorithm and others routing algorithms. (a) SimpleNet. (b) NSFNet. (c) ARPA-2.

Fig.5 show that in terms of blocking probability for different networks, our new ant-based algorithm is much better than the SP routing algorithm and also outperforms the FA routing algorithm. It is interesting to note in Fig.5 (a) that in a small network such as SimpleNet, the results of the AB

algorithm are only slightly better than the FA algorithm. The reason is that for the small network with a small average node degree of 2.7, there are only a few alternate routes between any two nodes.

The results in Fig.5 (b) indicate clearly that for a larger network with a bigger average node degree (such as NSFNet backbone), the AB algorithm significantly outperforms both the SP and FA algorithms. This is because the NSFNet network has a bigger average node degree of 3.0, so the AB algorithm has more chances to find a good path among more alternate routes, and thus can be more adaptive.

The comparisons in Fig.5 (c) show that for a large network with a relatively small average node degree (such as the APRA-2 network, with an average node degree of 2.4), the AB algorithm can still outperform the FA algorithm, but not very significantly. One reason is that there are only a few alternate routes (about two) between two nodes. Another reason is that the size of the network is relatively larger, so ants must take a longer time on their trips; this also prevents the Ant-based algorithm from achieving a better performance.

In all the tested networks, the AB algorithm slightly outperforms the FA algorithms when the traffic load is small. This is because there is not much difference between these routing algorithms when the network is slightly loaded. When the network is highly loaded, the same result is observed because ants cannot update the routing tables quickly enough when the network states change too fast. Overall, the AB is especially better than FA algorithms in the reasonable region of traffic load (the region in which the network is moderately loaded).

In summary, the above extensive simulation study based on different network topologies and various traffic loads has demonstrated that our AB algorithm has a very good adaptability, and that it consistently achieves a better performance in terms of low blocking probability when used for dynamic routing in WDM networks.

V. CONCLUSIONS

In this paper, we proposed an ant-based algorithm for the dynamic Routing and Wavelength Assignment problem in WDM networks with wavelength continuity constraint. In our algorithm, the ant-based agents continuously update the routing tables according to the network state. To enhance the performance of our new algorithm, we proposed an efficient scheme for scoring a path based on both the number of available wavelength and the path length, and also a scheme for path searching based on the second-highest value from the routing table entries. These new schemes can help an ant-based RWA algorithm overcome the stagnation problem, and thus effectively improve its performance in terms of blocking probability. A significant advantage of our new algorithm is that the path can be determined immediately based on the routing tables, significantly reducing set-up delay. Moreover, this new algorithm is flexible in the sense that to achieve a good performance, the number of ants can be

adjusted by their launching probability. Extensive simulation results upon different network topologies indicate clearly that our ant-based algorithm consistently outperforms the promising fixed-alternate routing algorithm. These attractive properties, especially the ability to guarantee both a low blocking probability and a short setup delay, make this new ant-based dynamic RWA algorithm very promising for the next generation of WDM networks supporting OCS and OBS.

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