Dynamic Wavelength Routing in WDM Networks via Ant Colony Optimization

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Abstract. This study considers the routing and wavelength assignment problem (RWA) in optical wavelength-division-multiplexed networks. The focus is dynamic traffic, in which the number of wavelengths per fiber is fixed. We minimize connection blocking using an ant-colony-optimization (ACO) algorithm that quantifies the importance of combining path-length and congestion information in making routing decisions to minimize total network connection blocking. The ACO algorithm achieves lower blocking rates than an exhaustive search over all available wavelengths for the shortest path.

A wavelength-routing all-optical network consists of wavelength-crossconnect nodes interconnected by fiber links. A set of individual network demands are routed from origin to destination (O-D) nodes, across these fiber links. The higher transmission capacity of all-optical networks is accomplished, in part, by sending multiple signals simultaneously through the same fiber-optic cable using wavelength-division multiplexing (WDM), which transmits multiple data streams simultaneously on different frequencies, or wavelengths.

1 Problem Definition

In wavelength-routed WDM networks, lightpaths are established between nodes and can span multiple fiber links in the network. A *lightpath* is realized by allocating a wavelength on each link comprising a path between two nodes. In the absence of wavelength-conversion equipment, a lightpath must occupy the same wavelength on all of its links, a property known as the *wavelength continuity constraint*.

Once a network is designed, the routing and wavelength-assignment problem (RWA) determines a set of lightpaths to carry the designated communications traffic. In the *static RWA problem*, all lightpath requests are known in advance, and the objective is to minimize the network resources required to satisfy all demands. The focus of this study is the *dynamic RWA problem*, in which lightpath requests arrive dynamically, and the number of wavelengths is limited. The objective is to minimize connection blocking. The optimal RWA problem is NP-complete [2], and thus is suited to heuristic methods.

Although the RWA problem has been studied extensively, this paper introduces a new algorithm for evaluating potential routes based on length and congestion information. Ant-colony optimization (ACO) as a method for routing and wavelength assignment on all-optical networks is introduced, and provides valuable insight on the length-versus-congestion tradeoffs. While ACO has been applied to the static RWA problem, this is its first use for the dynamic case. ACO is used to test the hypothesis that occasionally choosing slightly longer paths with less congestion improves blocking performance. ACO provides an effective testing platform for investigating the efficacy of unconstrained dynamic routing, by using ants that prefer paths with lower levels of network traffic.

This study decreases blocked requests by quantifying the importance of using congestion information. When confronted with a shorter path carrying more traffic or a slightly longer path with less congestion, the question of how much additional path length is acceptable to avoid congestion is examined.

2 Background and Previous Research

In [4], ACO is applied to the static routing and wavelength assignment problem and provides a background for the ACO approach to the dynamic RWA presented in this paper. In each algorithmic time step, ants move from each demand origin to each destination. Varela introduced backtracking, with each ant keeping a "tabu" list [6] of previously visited nodes. Backtracking avoids dead-ends and cycles—an approach adopted in the ACO algorithms in this paper. When an ant finds itself blocked, it pops its current location from a list of visited nodes and attempts to proceed from the previous location. This ability requires each ant's memory to contain a list of nodes visited in order.

Each ant in [4] maintains its own type of pheromone, and while ants are attracted to their own pheromone, they are repulsed by the pheromone of other ants in order to obtain even loading. The best results are achieved through a global update wherein ants are increasingly repulsed by paths on which more ants have traversed. Maintaining an ant and pheromone type for each connection request is time consuming, however.

All work in this paper focuses on extensions of work done on the dynamic RWA problem. The previous studies have focused on k-shortest-path-based routing schemes [1, 3]. More recent developments have incorporated congestion information into routing decisions [5, 8, 12].

Previous research tested the effectiveness of incorporating congestion information by testing a k-shortest-path (*ksp*) algorithm against a single-shortest-path strategy [7]. This work showed that a *ksp* algorithm achieves lower blocking than a strategy in which only a single path is available.

Chan and Yum [8] compare two routing strategies: routing connection requests on the shortest path with available capacity and on the least-loaded route from source to destination. Since the latter paths may be significantly longer, the shortest-routing strategy almost always provided lower blocking. A goal of this paper is to combine these two strategies into a routing algorithm that chooses

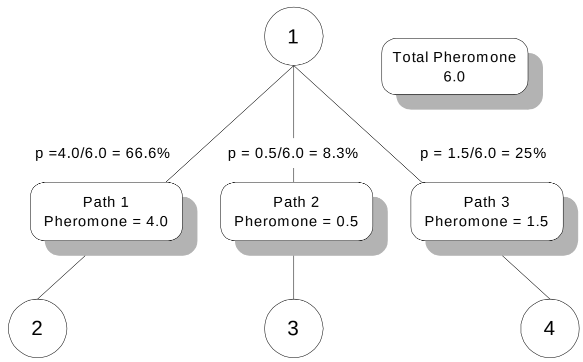


Fig. 1. Example path selection probabilities for an Ant at Node 1

short paths with low congestion, in an effort to improve performance over each strategy individually.

3 Ant-Colony Optimization

In the ACO algorithm introduced in this paper, an ant's "life" begins randomly at either the origin or destination node of the demand. It proceeds until it finds the corresponding destination or origin node, using a selected available wavelength. Each ant chooses its wavelength according to parametric rules such as most-used or random selection. At the completion of its search, the ant deposits pheromone along the path. In addition, each ant has memory of all nodes previously visited. Subsequent ants proceed similarly, choosing each vertex in their search paths based probabilistically on the level of pheromone on the connecting link, as shown in Figure 1 and described below.

We use the following notation: N is number of ants per connection request; L the set of links available from the current node; ϕ the normalized weight of length vs. weight of number of available wavelengths; l a link compromising a path P; l_c the total capacity in wavelengths of link l; l_a the set or available wavelengths on link l; and ψ_l the level of pheromone on link l. The probability γ that an ant will take a path l is the pheromone on that path normalized over the pheromone on all links available from the current node is $\gamma_l = \psi_l / \sum\limits_{i \in L} \psi_i$.

Pheromone is deposited on a per-demand basis. The pheromone matrix is reset once the final selection of wavelength and route is made for a connection request. This requires only one type of pheromone and avoids much of the overhead found in the implementation of the static case in [4], which requires running times on the order of hours. Even loading is achieved by having more pheromone deposited on paths that fewer previously routed O-D pairs occupy.

The shortest path found with the highest pheromone is selected as the best and final route for the demand. It is important to note that this may not be the shortest available path.

A global pheromone update is performed after each ant completes a route. The shortest path found receives pheromone in inverse proportion to its length. We also favor paths that have the fewest conflicts with demands already routed. Therefore, a component of pheromone update includes more pheromone for paths with more available wavelengths. Global update is assigned based on the following equations.

The sum of available lane quantity ratios for a path P is defined as $A_P = \sum_{l \in P} \frac{l_a}{l_c}$, with the mean available lane ratio for a path P of $M_P = \frac{A_P}{|P|}$. The pheromone value on link l at time-step t, given as ψ_l^t, is updated according to Equation 1 where the scalar parameter ϕ , $0 \leq \phi \leq 1$, controls the emphasis on path length versus available-lane ratio.

$$\psi_l^{t+1} = \psi_l^t + \frac{\phi}{|P|} + M_P(1 - \phi), \forall l \in P \tag{1}$$

Although each ant initially chooses a wavelength, the final wavelength selection is not made until all ants have completed a tour from source to destination for this connection request. The best route after N ants is found. Among the contiguous wavelengths available along this path, one is selected based on the most-used, first-fit, or random wavelength selection policy.

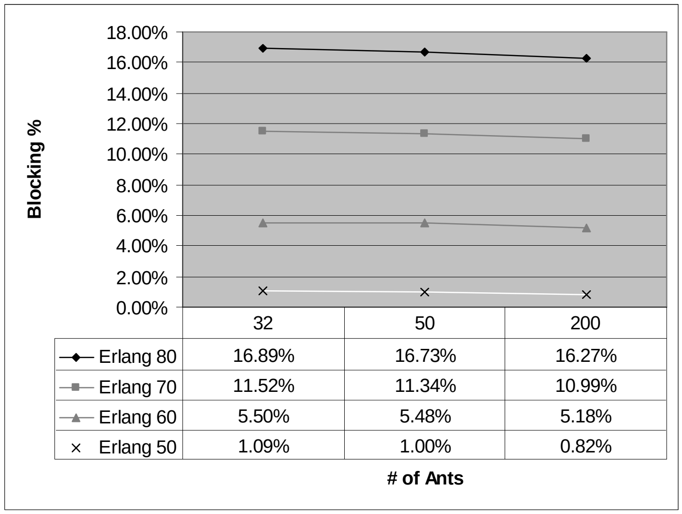
4 Computational Experiments and Analysis

For purposes of performance comparison, network blocking is the primary focus. Hereafter, general references to the performance of a particular heuristic refer to the percentage of blocked connection requests calculated during a simulation.

In all tests, connection-request arrival and duration rates follow a Poisson distribution with a mean of λ. All tests were conducted for 5x10^5 demands at each Erlang. Load is measured in Erlang for the entire network, as in [1]. If network traffic is modeled at 50 Erlang, and the 51st connection request arrives, a random existing connection is broken and its resources freed. Testing was conducted on the well-known 21-node, 26-link ARPA-2 network [7], with each edge in the network having an assumed capacity of 16 wavelengths.

Parametric Tests. The first test conducted concerned the wavelength-selection method. Random wavelength selection provided the lowest blocking at 50 ants, but performance for random selection peaked at this N. At 200 ants, most-used was the preferential method, outperforming first-fit and random at all traffic levels. In both tests, differences in blocking were small and details are omitted for brevity. However slight the differences in performance between wavelength selection methods, most-used was the method employed in all subsequent ACO tests.

The next set of tests concerned measuring blocking at several levels of N, for a fixed ϕ of 0.50. Performance will only improve up to a certain number of ants, although reductions in blocking percentages were seen at 200 ants. Significant processing is required with $N = 200$, however this increased processing load is



	32	50	200
Erlang 80	16.89%	16.73%	16.27%
Erlang 70	11.52%	11.34%	10.99%
Erlang 60	5.50%	5.48%	5.18%
Erlang 50	1.09%	1.00%	0.82%

Fig. 2. Blocking % vs. N, for $\phi = 0.5, l_c = 16$, and *most-used* selection rule

easily distributed, a strength of the ACO algorithm. Results of 32, 50, and 200 ants are presented in Fig. 2 for four traffic levels. Two hundred ants provided the best performance in all situations, and is the N value used for comparisons with other algorithms in the next section.

Comparisons with Published Algorithms. Mokhtar and Azizoglu present several heuristic RWA algorithms in [7]. 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 ACO algorithms in this paper.

The ACO algorithm at various parameters was compared with this algorithm, with the results displayed in Fig. 3. Using 200 ants, ACO provides the best results, outperforming the shortest available path at every traffic load. A ϕ value of 0.80 provided the best results in all but one case. At 70 Erlang, using no congestion information provided the best results by a slight margin. These results seem to indicate that while short paths are important, the best solution incorporates congestion information in selecting the route for each connection request. With a $\phi = 1$, congestion information is ignored, and the algorithm searches exclusively for the shortest path. However, since an initial pheromone value (ψ) of 1.0 is present on all edges in the network, ants may not find the shortest possible path.

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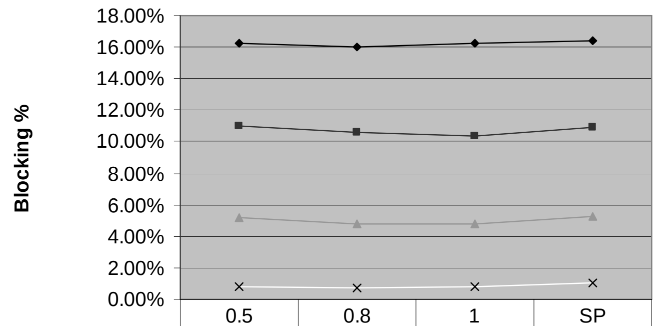

	0.5	0.8	1	SP
Erlang 80	16.26%	16.00%	16.21%	16.37%
Erlang 70	10.99%	10.59%	10.32%	10.88%
Erlang 60	5.18%	4.78%	4.80%	5.26%
Erlang 50	0.82%	0.74%	0.77%	1.04%

Algorithmic parameters

Fig. 3. ϕ and Shortest-Path Comparison, for $N = 200, l_c = 16$, and *most-used* rule

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