Engineering Applications of Artificial Intelligence 24 (2011) 295–305

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Ant colony optimization for dynamic routing and wavelength assignment in WDM networks with sparse wavelength conversion

Ming-Tsung Chen [a,c], Bertrand M.T. Lin [b,*], Shian-Shyong Tseng [c,d]

[a] Telecommunications Strategy and Marketing Research Department, Telecommunication Laboratory, Chunghwa Telcom Co., Ltd., Taiwan
[b] Institute of Information Management/Department of Information and Finance Management, National Chiao Tung University, Taiwan
[c] Department of Computer and Information Science, National Chiao Tung University, Taiwan
[d] Department of Information Science and Applications, Asia University, Taiwan

A R T I C L E I N F O

Article history:
Received 17 November 2009
Received in revised form
28 May 2010
Accepted 31 May 2010
Available online 22 June 2010

Keywords:
Routing and wavelength assignment
Communication cost
Delay bound
Approximate solution
Ant colony optimization

A B S T R A C T

Since optical WDM networks are becoming one of the alternatives for building up backbones, dynamic routing, and wavelength assignment with delay constraints (DRWA-DC) in WDM networks with sparse wavelength conversions is important for a communication model to route requests subject to delay bounds. Since the NP-hard minimum Steiner tree problem can be reduced to the DRWA-DC problem, it is very unlikely to derive optimal solutions in a reasonable time for the DRWA-DC problem. In this paper, we circumvent to apply a meta-heuristic based upon the ant colony optimization (ACO) approach to produce approximate solutions in a timely manner. In the literature, the ACO approach has been successfully applied to several well-known combinatorial optimization problems whose solutions might be in the form of paths on the associated graphs. The ACO algorithm proposed in this paper incorporates several new features so as to select wavelength links for which the communication cost and the transmission delay of routing the request can be minimized as much as possible subject to the specified delay bound. Computational experiments are designed and conducted to study the performance of the proposed algorithm. Comparing with the optimal solutions found by an ILP formulation, numerical results evince that the ACO algorithm is effective and robust in providing quality approximate solutions to the DRWA-DC problem.

1. Introduction

Optical networks are a type of high-capacity telecommunication networks that can provide routing, grooming, and restoration at wavelength level (Green, 1992). The technology of *Wavelength Division Multiplexing* (*WDM*) networks is mainly based on optical wavelength-division multiplexing on optical fibers for forming a number of multi-communication channels at different wavelengths with an electronic processing speed (Lowe, 1998). WDM networks provide connectivity among optical components to let optical communication meet the increasing demands for high channel bandwidths and low communication delays. The utilization of wavelengths to route data is referred as wavelength routing, and an optical switch employing the technique is referred as a wavelength-routing switch. Therefore, in a wavelength-routing WDM network that is constructed using optical fiber links to connect input ports and output ports in wavelength-routing switches, data can be routed to other optical switches based on wavelengths of optical fibers. If the transmission between input port and output port involves two different wavelengths, the switch should have the capacity of wavelength conversion (Ramamurthy and Mukherjee, 1998) and gives rise to transmission delay and deployment cost. Deploying a part of switches with wavelength conversion in networks can be a viable alternative to balance the cost of constructing networks and network efficiency. Networks of this type are referred as WDM networks with sparse wavelength conversion.

In (wavelength-routing) WDM networks, a light-path (Chlamtac et al., 1992) can be set up in a similar way as a circuit-switched network to carry data among switches at wavelength level without optical-to-electrical and electrical-to-optical conversions, and then the data can be transmitted according to the trail of the light-path. Since different set-up light-paths will occupy different resources (e.g., switches, wavelengths) and end-to-end transmission time in network communication, the communication cost and the transmission delay of a light-path are usually used as the criterion for evaluating the efficiency of a light-path. The communication cost may be the numbers or the costs of utilized fibers and switches included in a light-path. The transmission delay is the sum of transmission delays of all switches and links in the light-path. The routing and

* Corresponding author. Tel.: +886 3 5131472.
E-mail addresses: bmtlin@mail.nctu.edu.tw, bmtlin@iim.nctu.edu.tw (B.M.T. Lin).

0952-1976/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2010.05.010

wavelength assignment (RWA) problem known to be NP-hard (Karasan and Ayanoglu, 1998) is defined as follows: Given a set of connection requests, each of which is specified to transmit data from a source to a destination, the problem is to find a light-path from the source to the destination for each request and to assign a wavelength to each link included in the light-path.

The RWA problem can be categorized into two types, static RWA (SRWA) and dynamic RWA (DRWA). The SRWA problem is to determine the logical topology which can be used to configure all switches according to the found light-paths and assigned wavelengths in the given network. The objective is usually to maximize the routing throughput (Krishnaswamy and Sivarajan, 2001) or to minimize the number of required wavelengths. The DRWA counterpart is an on-line version in which connection requests arrive one at a time, and the requests must be routed in real time under the current environment of the network. For minimizing blocking probability (Shen et al., 2001; Qin et al., 2003; Ngo et al., 2006) and wavelengths, the objective is to find a survival light-path when some links fail, and to maximize the carried traffic (Kavian et al., 2007). For setting up and tearing down light-paths to minimize the number of blocked connections, a distributed control scheme for establishing reliability-constrained least-cost light-paths and four heuristics were proposed in Saradhi et al. (2007).

Many new network applications, such as videoconferencing, video on demand system, on-line gaming, etc., have inspired the demands for new communication models. Moreover, to guarantee that video and audio signals can be efficiently transmitted in interactive multimedia applications, transmission delays from a source to a destination will be limited under a given delay bound, where the delay bound may be decided according to the degree of emergence, data priority, or application type of data. Therefore, transmitting data with delay bound constraints is realistic to reflect the demand about data transmission in the future. A request with delay bound dictates that it needs to be successfully transmitted before its given delay constraint is violated. The issue of routing this type of requests is referred as the RWA with delay constraints problem (RWA-DC) in WDM networks.

In most cases, switches with wavelength conversion are reserved to provide the imperative of converting wavelength in the light-path such that the data can be successfully transmitted. In order to avoid using this type of switches in the light-path not requiring wavelength conversion, it is necessary to incur extra costs for using this type of switches. Although most of previous research neglected the communication cost of wavelength conversion in switches so as to simplify the problem and thus reduce the complexity, the communication cost of wavelength conversion is taken into consideration in this paper to ensure that the light-path can make better use of the switches without conversion capability. Besides, because transmission delay occurs in the case that wavelength is converted in a switch with wavelength conversion, it is therefore crucial to take transmission delay into account. In this paper, we assume communication cost and transmission delay in switches are incurred when the wavelength is converted between the input and output ports. In summary, the dynamic RWA-DC (DRWA-DC) problem involves the following three features: (1) some of the switches can provide wavelength conversion, (2) data transmission through switches using different wavelengths at input and output ports incurs communication cost and transmission delay, and (3) requests are associated with delay bounds. The goal is to minimize the total communication cost.

For the RWA problem, Karasan and Ayanoglu (1998) proved the NP-hardness. Integer linear programming (ILP) models (Krishnaswamy and Sivarajan, 2001), statistics (Ngo et al., 2006), and meta-heuristics including heuristics (Shen et al., 2001; Qin et al., 2003) and genetic algorithm (GA) (Kavian et al., 2007) were proposed to cope with different problem settings. Although the ILP model can be deployed to find optimal solutions, the execution time is not affordable for large-scale networks. Moreover, the DRWA-DC problem exhibits much more complicated structures; it is unlikely to follow the ILP approach to produce optimal solutions in an acceptable time.

In this paper, we address a design of ant colony optimization (ACO), which is a meta-heuristic developed in the early 1990s (Dorigo et al., 1991). The ACO uses natural metaphor inspired by the behavior of ant colonies to solve complex combinatorial optimization problems for finding near-optimal solutions. It has demonstrated significant strengths in many application areas, such as the traveling salesman problem (Dorigo and Gambardella, 1997), generalized minimum spanning tree problem (Shyu et al., 2003), scheduling problems (Shyu et al., 2004a; Lin et al., 2008; Udomsakdigool and Kachitvichyanukul, 2008; Sabuncuoglu et al., 2009), optimization of chaotic systems (Wang and Ip, 2005), minimum weight vertex cover problem (Shyu et al., 2004b), layout design of satellite modules (Sun and Teng, 2003), assembly line balancing (McMullen and Tarasewich, 2006), and distributed optimization of a logistic system (Silva et al., 2006), just to name a few. The details of the ACO design for solving the RWA problem will be described later.

In Varela and Sinclair (1999), Garlick and Barr (2002), and Kwang and Weng (2003), the ACO has been used to solve the RWA problem, but communication cost, wavelength conversion cost and delay bound were not incorporated in their studies. To the best of our knowledge, Varela and Sinclair (1999) is the first paper applying the ACO to cope with the SRWA problem. In their design, each ant keeps a tabu list of previously visited nodes to avoid dead-ends and cycles and to allow backtracking, where backtracking means that an ant will reversely pop out its previous location to alter the visited nodes when the already found partial tour is blocked. Garlick and Barr (2002) extended the ACO application to the DRWA problem by using length and congestion information in making routing decisions to reduce the possibility of network blocking in the tour-constructing phase. In Kwang and Weng (2003), a survey and comparison on ACO applications to routing and load-balancing issues were presented. Varela and Sinclair (1999) and Garlick and Barr (2002) both used the shortest path algorithm and the minimum number of edges of paths to find a light-path as the heuristic ingredient of the ACO. However, delay bounds make these heuristics inappropriate for solving the DRWA-DC problem. Moreover, the realistic concerns about wavelength conversion in switches give rise to a more complicated problem. According to the three characteristics: delay bound, wavelength conversion, and objective function, Table 1 shows the comparisons of previous research papers: Krishnaswamy and Sivarajan (2001), Shen et al. (2001), Garlick and Barr (2002), Qin et al. (2003), Ngo et al. (2006), and Kavian et al. (2007).

The DRWA-DC problem is relatively difficult because many issues need to be simultaneously taken into account: the request is associated with a delay bound, the parts of switches have a wavelength conversion capability, and a light-path is evaluated by communication cost and wavelength conversion cost. Since the DRWA-DC problem is computationally challenging, it is very unlikely to optimally solve it in polynomial time. While the ACO has been applied to solve some specific RWA, no results have been reported to the complex, but realistic, problem involving delay bound and wavelength conversion simultaneously. In this paper, we shall design new ACO features to produce solutions to the studied problem.

The rest of this paper is organized as follows. Section 2 is dedicated to a formal formulation of the DRWA-DC problem. In Section 3, we shall introduce the basic structure of the ACO and

Table 1
Comparisons of related research.

	Delay bound	Wavelength conversion	Objective
Krishnaswamy and Sivarajan (2001)	No	No	Maximizing the number of connections and minimizing the number of required wavelengths
Shen et al. (2001)	No	Yes	Minimizing the blocking probability
Garlick and Barr (2002)	No	No	Minimizing the blocking connections
Qin et al. (2003)	No	Yes	Maximizing the number of connections and reducing the number of required conversions
Ngo et al. (2006)	No	No	Minimizing the blocking probability
Kavian et al. (2007)	Yes	No	Maximizing the number of connections
This paper	Yes	Yes	Minimizing the communication cost of a connection

then present several features that can nicely shape the DRWA-DC problem into a graph-based framework that is suitable for the development and application of ACO algorithms. Section 4 is dedicated to the computational experiments designed to evaluate the performance of the proposed ACO algorithm. Numerical results and analysis are also included. Section 5 summarizes the results and gives some concluding remarks.

2. Problem formulation

Before proceeding to the problem statements and formulation, we introduce the notation that will be used throughout this paper.

Notation

- W set of wavelengths available for data transmission in the given WDM network
- n number of nodes in the WDM network
- m number of different wavelengths in W
- I_i wavelength label at the input port of node i
- O_i wavelength label at the output port of node i
- $r(s, d, \Delta)$ transmission request r from source s to destination d subject to delay bound Δ
- e_{ij} directed edge from node i to node j
- e_{ijl} directed wavelength link of wavelength l on e_{ij}
- $c(e_{ij})$ communication cost on e_{ij}
- $d(e_{ij})$ transmission delay on e_{ij}
- $\hat{c}(i)$ wavelength conversion cost at node i
- $\hat{d}(i)$ wavelength conversion delay at node i
- $T_c(e_{ijl})$ communication cost for routing from node i to node j using wavelength l
- $T_d\ (e_{ijl})$ transmission delay for routing from node i to node j using wavelength l
- w_i binary variable dictating whether node i provides wavelength conversion or not; i.e., $w_i=1$, if yes; 0, otherwise
- λ_{ijl} binary variable dictating whether wavelength link e_{ijl} is feasible or not to represent the wavelength l in e_{ij} can be to be used to transmit data or not, i.e., $\lambda_{ijl}=1$, if yes; 0, otherwise

A network is represented by a weighted graph $G(V, E)$, where V is the set of switches and set E contains directed edges corresponding to the directed optical links among the switches. $|V|=n$ denotes the number of nodes in the network. Binary variable w_i indicates whether the node $i\in V$ is associated with wavelength conversion, annotated by $w_i=1$ or 0. The directed edge from node i to node j is denoted by e_{ij}. $c(e_{ij})$ and $d(e_{ij})$ represent the communication cost and the transmission delay of edge e_{ij}, respectively. At node i, wavelength communication cost and wavelength transmission delay are denoted by $\hat{c}(i)$ and $\hat{d}(i)$, respectively. The set of wavelengths available on the optical links is denoted by W with cardinality $|W|=m$ as the number of different wavelengths. The m wavelengths on each e_{ij} can be viewed as m wavelength links e_{ijl}, $1\le l\le m$, to represent the wavelength-based connections, where $c(e_{ijl})=c(e_{ij})$ and $d(e_{ijl})=d(e_{ij})$. Therefore, when a light-path includes two wavelength links e_{ijl} and $e_{jkl'}$ $(l\neq l')$, the switch j must provide the wavelength conversion capacity such that the signal passing from e_{ij} to enter the input port of j using wavelength l can be transmitted to switch k from the output port of j using wavelength l'.

A request under a delay bound Δ is represented by $r(s, d, \Delta)$ indicating that there is data originating from source s to be routed to destination d and the transmission delay of the complete routing session from s to d must be smaller than or equal to the delay bound Δ. Each request may be different from any of the others in respects of different sources, different destinations, and different delay bounds, which usually are determined by its priority, degree of emergence or other criteria.

The DRWA-DC problem seeks to find an assigned light-path P that consists of a sequence of connected wavelength links. Let variables I_i and O_i represent the used wavelength labels at the input and output ports passing through switch i, respectively. The transmission delay passing through switch i is $\left\lceil\frac{|I_i-O_i|}{m}\right\rceil\hat{d}(i)$, where $\left\lceil\frac{|I_i-O_i|}{m}\right\rceil$ is 0 or 1 depending on whether $I_i=O_i$ or not; that is, the transmission delay $(\hat{d}(i))$ exists only in the case that the wavelengths are different between input and output ports $(I_i\neq O_i)$. Considering wavelength conversion in general, the communication cost $T_c(e_{ijl})$ and the transmission delay $T_d(e_{ijl})$ of using wavelength link e_{ijl} to node j could be calculated as follows:

$$T_c(e_{ijl})=\begin{cases}\infty & \text{if } w_i=0 \text{ and } l\neq I_i,\\ c(e_{ijl})+w_i\left\lceil\dfrac{|I_i-l|}{m}\right\rceil\hat{c}(i) & \text{otherwise,}\end{cases} \tag{1}$$

$$T_d(e_{ijl})=\begin{cases}\infty & \text{if } w_i=0 \text{ and } l\neq I_i,\\ d(e_{ijl})+w_i\left\lceil\dfrac{|I_i-l|}{m}\right\rceil\hat{d}(i) & \text{otherwise}\end{cases} \tag{2}$$

The formula is computed based on the used wavelength links to reduce the complexity. Therefore, the overall communication cost and the transmission delay incurred in the assigned light-path P are $c(P)=\sum_{e_{ijl}\in P}T_c(e_{ijl})$ and $d(P)=\sum_{e_{ijl}\in P}T_d(e_{ijl})$, respectively. The assigned light-path P will be a feasible solution for routing the request $r(s, d, \Delta)$ when the following three conditions are all satisfied:

(1) the origin of P is s;
(2) the destination node of P is d; and
(3) the transmission delay of P is no greater than the delay bound (i.e., $d(P)\le\Delta$).

In the rest of paper, for notational convenience, assigned light-path and feasible solution will be replaced with light-path and solution if no confusion would arise.

3. ACO design for DRWA-DC

In this section, we develop several features for the deployment of the ACO. The notation used in our ACO design is given in the following:

b	number of ants
ξ	percentage of the b ants to distribute at s and d
A_k	set of nodes accessible to ant k
$\overline{\tau}_{ijl}$	initial pheromone on wavelength link e_{ijl}
τ_{ijl}	dynamic desirability measure (pheromone intensity) on wavelength link e_{ijl}
η^k_{ijl}	static desirability measure about link e_{ijl} based on a heuristic value for ant k
p^k_{ijl}	probability that ant k moves from node i to node j using wavelength l (i.e., using e_{ijl})
P^k	light-path traversed by ant k
$c(P^k)$	communication cost of P^k, $c(P^k)=\sum_{e_{ijl}\in P^k} T_c(e_{ijl})$
$d(P^k)$	transmission delay of P^k, $d(P^k)=\sum_{e_{ijl}\in P^k} T_d(e_{ijl})$

The ACO is a family of meta-heuristics that are inspired by the natural optimization mechanism conducted by real ants. The general framework of the ACO algorithm is shown in Fig. 1. In the ACO framework, the underlying environment for the ant colony to explore through is a directed graph, possibly with weights assigned to the edges. Therefore, a studied problem is usually represented by a weighted graph. The ACO system starts by distributing a set of artificial ants onto the graph. Each ant will construct a tour that corresponds to a solution to the original problem. When all ants attain solutions, they share their information via pheromone and then next iteration commences. The process is repeated until some pre-specified criterion is satisfied. The optimization mechanism of the above-mentioned process is carried out by two important features: state transition rules and pheromone updating rules. A state transition rule is used for an ant to determine which node it will visit next (Step 2.2.1). The pheromone updating rules dynamically updates the pheromone intensities (or, in simple words, the degree of preference) on the edges (Steps 2.2.2 and 2.3). For general discussion on the philosophy and design detail, the reader is referred to Dorigo et al. (1991).

Although the ACO has been applied to deal with SWRA (Varela and Sinclair, 1999) and DRWA (Garlick and Barr, 2002), these proposed approaches do not work for the DRWA-DC problem. For example, the backtracking method for avoiding dead-ants in Varela and Sinclair (1999) and Garlick and Barr (2002) cannot be used in DRWA-DC because transmission delays need to be taken into account. The existence of delay bounds of requests stipulates the global pheromone updating rule to test whether some ants arrive at the destinations successfully qualifying by the delay bound. In this section, we propose and design an ACO algorithm that can produce approximate solutions with all the addressed realistic constraints incorporated.

3.1. Initialization of ACO

In our ACO design for the DRWA-DC problem, the initialization phase includes two parts, dispatching ants to nodes and initializing pheromone on edges. For the first part, the trail of an ant can be viewed as a light-path. Therefore, it is reasonable to expect that an ant will start from the source and stop at the destination of the request. The optimal trail with the minimum communication cost indicates that it is an optimal routing light-path for the request. The strategy that finds trails from source towards destination is called forward searching. On the other hand, backward searching refers to the strategy starting from the destination. Combining both strategies, we can let the ants begin their searching sessions randomly at either the source s or the destination d. In this paper, parameter ξ is given to adjust the percentage of b ants to be initially dispatched to s; that is, the numbers of ants initially positioned at the source and the destination are ξb and $(1-\xi)b$, respectively.

For the second initialization task, applying some heuristics will provide informative guidance to determine the initial pheromone, and possibly shorten the time required by finding a near optimal or even optimal solution. Considering the objective of minimizing the total communication cost of routing a given request, the initial pheromone $\overline{\tau}_{ijl}$ on each wavelength link e_{ijl} is defined as

$$\overline{\tau}_{ijl}=\begin{cases}0 & \text{if } \lambda_{ijl}=0,\\ 1+\dfrac{1/c(e_{ijl})}{\sum_{x\in V}(\lambda_{ixl}/c(e_{ixl}))} & \text{if } \lambda_{ijl}=1.\end{cases} \tag{3}$$

Recall the definition of $\lambda_{ijl}=0$, which indicates that wavelength link e_{ijl} is infeasible. In order to prevent an ant from traversing an infeasible wavelength link, the initial pheromone of that wavelength link is set to 0 (Eq. (3)). If the wavelength link is viable, the initial pheromone will be set as in Eq. (3) to let a wavelength link with less communication cost have a higher intensity of initial pheromone than the others.

3.2. State transition rule

The state transition rule presented in this paper features the following two aspects. First, unlike the ACO research (Shyu et al., 2004b) proposed solutions through the exploration of the power

Step 1: Initialization of ACO
Step 2: Repeat
    2.1. Each ant is positioned at some node
    2.2. Repeat
        2.2.1. Each ant moves to a next node according to the state transition rule
        2.2.2. Apply the local pheromone updating rule
    Until all ants have constructed a complete tour or encountered a dead-end
    2.3. Apply the global pheromone updating rule
Until the stopping criterion is met

Fig. 1. ACO framework.

set of the vertex set, the solution in this paper will obtain a path of wavelength links from the source to the destination. Depending on whether the switches provide wavelength conversion or not, each ant can choose wavelength links using the same or different wavelengths to route data to the next switch. That is, the solution to DRWA-DC can be viewed as a sequence of wavelength links, and the preference information (including pheromone intensity and local heuristic value) is deposited on the wavelength links. Secondly, the local heuristic used in most of previous research is static (that is, the value will not change during the optimization process). Shyu et al. (2004b) deployed a dynamic heuristic to reflect the situation that the access preference for a wavelength link changes over time depending on which wavelength links have been already selected. Due to the above concerns, we modify the state transition rule defining the probability that ant k at node i uses wavelength link e_{ijl} to route data to node j as follows:

$$p_{ijl}^{k}=\begin{cases}1 & \text{if } q<q_0 \text{ and } \langle j,l\rangle=\arg\max_{r\in A_k,t\in W}\{\lambda_{\mathrm{irt}}\tau_{\mathrm{irt}}(\eta_{\mathrm{irt}}^{\mathrm{k}})^{\beta}\},\\ 0 & \text{if } q<q_0 \text{ and } \langle j,l\rangle\neq\arg\max_{r\in A_k,t\in W}\{\lambda_{\mathrm{irt}}\tau_{\mathrm{irt}}(\eta_{\mathrm{irt}}^{\mathrm{k}})^{\beta}\},\\ \dfrac{\lambda_{ijl}\tau_{ijl}(\eta_{ijl}^{k})^{\beta}}{\sum_{r\in A_k}\lambda_{irl}\tau_{irl}(\eta_{irl}^{k})^{\beta}} & \text{if } q\geq q_0,\end{cases} \tag{4}$$

where A_k denotes the set of accessible nodes for ant k to visit such that no node can be traversed for more than once, τ_{ijl} is the dynamic desirability measure about the access to the wavelength link e_{ijl}, η_{ijl}^{k} is the static desirability measure about the same wavelength link based on a problem-specific local heuristic, and β is the parameter controlling the relative significance between the two measures. Following the same line of reasoning in Eq. (3), λ_{ijl} is added to each equation to guarantee that any infeasible wavelength link, i.e., λ_{ijl}=0, cannot be chosen.

The value of p_{ijl}^{k} can be decided according to a random number q drawn from the open interval (0, 1). If q is less than a specified threshold q_0, the wavelength link e_{ijl} with the maximal product $\lambda_{irt}\tau_{irt}(\eta_{irt}^{k})^{\beta}$ is always selected (see Eq. (4)); otherwise, the wavelength link is selected according to the probability given in Eq. (4). That is, the state transition rule is a controlled trade-off scheme between the exploitation search and the exploration search of the problem space. Note that the probability value p_{ijl}^{k} depends on which wavelength link the ant uses to construct the light-path (trail) and that the transmission delay of the light-path is constrained by the delay bound. When the trail exceeds the delay bound, the value of η_{ijl}^{k} will be set to be 0 in Eq. (5), which will be defined in the next paragraph. Therefore, such a wavelength link will not be selected in Eq. (4). It thus highly suggests that the quality and feasibility of a solution depend on the wavelength links selected; that is, the communication cost and the transmission delay of light-path reflect the quality of the solution found by some ant and whether the solution is feasible or not, respectively. The value of variable τ_{ijl}, which gradually reflects the global preference for link e_{ijl}, is updated according to the quality of the final solution constructed at the end of each cycle and will be described in the next subsection. Local preference is incorporated to reflect the objective of communication cost minimization subject to transmission delay bounds. When there is no feasible solution found by the ant colony, determining a feasible solution, if exists, becomes more crucial. Therefore, the local preference needs to reflect the status of whether a feasible solution has been found thus far. During the solution-seeking session, if no feasible solution has been encountered, the local preference will center on how to find a feasible solution according to the transmission delays of links; otherwise, the aspect of communication cost is considered. Therefore, the value of variable η_{ijl}^{k}, which evaluates the local preference of ant k for wavelength link e_{ijl}, changes dynamically and is given by

$$\eta_{ijl}^{k}=\begin{cases}0 & \text{if } d(\mathrm{P}^{k})+T_d(e_{ijl})>\Delta,\\ \dfrac{\lambda_{ijl}}{T_d(e_{ijl})} & \text{if no feasible solution has been found,}\\ \dfrac{\lambda_{ijl}}{T_c(e_{ijl})} & \text{otherwise,}\end{cases} \tag{5}$$

where η_{ijl}^{k} can be seen as the inverse value of transmission delay (Eq. (5)) or the inverse value of communication cost (Eq. (5)), depending on whether the ACO system has explored some feasible solution or not. In the sequel, the proposed dynamic local heuristic favors the feasible wavelength link that has either minimum transmission delays or minimum communication costs.

3.3. Pheromone updating rule

In the proposed system, we apply global and local pheromone updating rules as follows. First, at the end of each cycle we keep track of the best feasible solution P^{best} and the worst infeasible solution P^{worst} encountered by the colony. Our idea is to encourage the ants to follow links in P^{best} and avoid links in P^{worst} in the following cycles. This idea is realized by reinforcing (respectively, lessening) the intensities of the pheromone currently left on the wavelength links in P^{best} (respectively, P^{worst}). The pheromone τ_{ijl} on wavelength link e_{ijl} is updated according to the following global updating rule:

$$\tau_{ijl}=(1-\rho)\tau_{ijl}+\rho\sum\nolimits_k\tau'_{ijl}-\rho\sum\nolimits_k\tau''_{ijl}, \tag{6}$$

where

$$\tau'_{ijl}=\begin{cases}\dfrac{1/T_c(e_{ijl})}{\sum_{e\in P^{best}}\dfrac{1}{T_c}(e)} & \text{if } e_{ijl}\in P^{best},\\ 0 & \text{otherwise,}\end{cases} \tag{7}$$

and

$$\tau''_{ijl}=\begin{cases}\dfrac{T_d(e_{ijl})}{\sum_{e\in P^{worst}}T_d(e)} & \text{if } e_{ijl}\in P^{worst},\\ 0 & \text{otherwise}\end{cases}. \tag{8}$$

Parameter $\rho\in(0,\ 1)$ simulates the evaporation rate of the pheromone intensity and enables the algorithm to reduce the significance of inferior links or forget the bad decisions previously made.

Secondly, we activate the local pheromone updating rule to shuffle the solutions and prevent early convergence, i.e., all the ants make the same decisions. The local updating rule is performed at the end of each step when each ant selects a new wavelength link e_{ijl}. The pheromone intensity on link e_{ijl} is updated by

$$\tau_{ijl}=(1-\varphi)\tau_{ijl}+\varphi\overline{\tau}_{ijl}, \tag{9}$$

where $\varphi\in(0,\ 1)$ is a parameter adjusting the current pheromone previously laid on e_{ijl} and $\overline{\tau}_{ijl}$ is the initial value of pheromone laid on e_{ijl}. Note that the local updating rule decreases the pheromone intensity on the link just visited by an ant and makes the selected links less attractive to other ants. The effect of the process will direct the exploration session of an ant toward the links that have not yet been visited by other ants.

3.4. Stopping criterion

Like other meta-heuristics, different types of stopping criteria can be used for the ACO. We cite the following four for the reader's interest:

*C*1: The number of iterations is greater than a specified iteration limit.
*C*2: The execution time is longer than a specified CPU time limit.
*C*3: The averages of communication costs of ants in some consecutive iterations remain unchanged.
*C*4: The number of consecutive iterations in which no improvement attained on the incumbent solution is greater than a specified limit.

In this paper, we use the last one (*C*4) as the stopping criteria of our ACO design.

4. Computational experiments

This paper focuses on determining an assigned light-path of low communication cost such that switches in the network can be set up to route a request. To study the performance of the proposed approach, we designed and conducted a series of computational simulations. The scheme used in our simulation can be referred to Waxman (1988). In the scheme, there are n nodes randomly distributed over a rectangular grid with integer coordinates. In a network topology generated for experiments, each directed link from node u to node v is associated with the probability function $p(u,v)=\lambda\exp(-p(u,v)/\gamma\delta)$, where $p(u,v)$ is the coordinate distance between u and v, δ is the maximum distance between each two nodes, and λ and γ are control variables selected from interval (0, 1].

The communication cost from node u to node v is defined by taking the integer value of the distance between them on the grid. The transmission delay is an integer randomly generated from interval [1, 5]. For each request $r(s, d, \Delta)$, s and d are generated in a random manner. The delay bound Δ must be reasonable, for otherwise it is unlikely for a feasible light-path to be found. To generate a request with a reasonable delay bound, we use the value according to the minimum transmission delay between s and d found by applying Dijstra's shortest path algorithm (Dijstra, 1959), and set Δ to be equal to χ times of the derived minimum transmission delay, where χ is a control parameter dictating the tightness between delay bound and minimum transmission delay. In our experiments, we set $\lambda=0.7$, $\gamma=0.7$, and size of rectangular grid$=100$ to simulate the networks with different numbers of nodes. Moreover, 15% of the nodes are equipped with wavelength conversion. As for the parameters of the ACO algorithm, preliminary experiments suggest $\xi=0.5$, $\beta=1$, $\rho=0.7$, $\varphi=0.9$, and $q_o=\alpha=0.5$.

The experiments consist of three parts: (1) introduction of transmission delays to the ILP formulation (Chen and Tseng, 2003), (2) comparisons between the ACO algorithm and the ILP formulation, and (3) investigation on the number of iterations exerted in the ACO algorithm. The codes were written in C++. The platform is a personal computer with an Intel P4 2.4 GMHz CPU and 1 GB RAM.

4.1. Introduction of transmission delays to the ILP formulation

The ILP formulation used in the simulation to solve DRWA-DC is adapted from that proposed in Chen and Tseng (2003). It was implemented using the linear programming tool ILOG's CPLEX 7.1. Three types of networks were tested: 40 switches ($n=40$), 50 switches ($n=50$), and 60 switches ($n=60$), for each of which 200 different requests were randomly generated. Five wavelengths were provided for the networks. The delay bound was set to be χ ($\chi=3.0$, 2.0, 1.5, 1.4, 1.3, 1.2, 1.1) times of the minimum transmission delay between the source and the destination in each request. For each combination of values of χ and network types, the elapsed run times, each of which are averaged over 200 requests, are summarized in Table 2. The experimental results suggest that the elapsed execution times increase sharply as the number of switches grows or the delay bound becomes tighter (i.e., smaller values of χ). For example, when $\chi=1.1$, the average execution time is more than 1380 s. Therefore, the ILP formulation cannot solve the DRWA-DC problem well when the number of switches is more 70 or the specified delay bound of a request is close to the minimum transmission delay.

Table 2
Average execution time (s) for different χ values and different networks.

χ	$n=40$	$n=50$	$n=60$
3.0	0.216	0.369	1.987
2.0	0.583	0.682	3.496
1.5	1.463	1.691	9.889
1.4	2.245	4.192	19.382
1.3	3.664	9.758	55.751
1.2	4.679	10.746	79.421
1.1	32.789	395.394	1380.914

4.2. Comparisons between the ACO and the ILP formulation

In this part, we define the stopping criterion for the ACO algorithm to be that 2000 iterations are reached or the incumbent value is equal to the optimal one. The same experiment settings were also applied to observe the solutions found by the ACO approach. Experimental results are shown in Tables 3–5 for the networks with 40, 50, and 60 switches and different χ values, respectively. The solutions found by the ILP formulation are used as the baseline for comparisons. In these tables, the first two columns show the value of χ and the number of ants. We kept track of the scenarios of the ACO algorithm at iteration 1000 and iteration 2000. Recall that the algorithm will stop before entering later iterations if it encounters an optimal solution. Consider the major column entitled "1000 Iterations". Four sub-columns summarize the computational statistics at the end of the 1000th iteration:

#Fea: number of requests for which feasible solutions are found;
#Opt: number of requests that are optimally solved;
Dev: average communication cost deviation of the found solutions from the optimal ones; and
ET: average execution time.

Dev is defined as follows:

$$Dev=\frac{\sum_r c(P_r^{feas})-c(P_r^{opt})/c(P_r^{opt})\times 100\%}{\#Fea}, \tag{10}$$

where $c(P_r^{feas})$ and $c(P_r^{opt})$ are the communication cost of the feasible solution P_r^{feas} found at the end of some iteration in the ACO algorithm and the communication cost of the optimal solution P_r^{opt} found by the ILP formulation, respectively. The second part reports the results at the end of 2000 iterations. When the ACO algorithm finished processing 200 requests, we also keep

Table 3
Results of 200 requests routing in 40 nodes (n=40).

χ	b	1000 iterations				2000 iterations				Opt		Non-opt	
		#Fea	*#Opt*	*Dev* (%)	*ET*	*#Fea*	*#Opt*	*Dev* (%)	*ET*	*Iter*	*ET*	*Iter*	*ET*
3.0	20	200	156	1.49	0.654	200	169	0.70	1.045	205	0.463	619	4.218
	40	200	169	0.71	0.992	200	179	0.35	1.503	177	0.763	516	7.807
	60	200	178	0.37	1.132	200	184	0.26	1.604	128	0.767	390	11.236
	80	200	178	0.33	1.467	200	182	0.26	2.146	121	0.980	434	13.944
	100	200	185	0.26	1.190	200	190	0.15	1.655	92	0.854	344	16.870
2.0	20	200	153	4.39	0.558	200	163	3.74	0.906	229	0.403	429	3.124
	30	200	149	3.17	0.760	200	161	2.02	1.281	202	0.451	471	4.708
	60	200	164	1.45	1.046	200	174	1.00	1.668	166	0.714	264	8.052
	80	200	168	1.65	1.341	200	173	1.29	2.082	138	0.820	390	10.171
	100	200	172	0.98	1.346	200	180	0.62	2.149	133	0.941	405	13.021
1.5	20	199	152	3.73	0.438	200	161	2.31	0.748	174	0.235	513	2.868
	40	199	161	2.34	0.699	200	170	1.69	1.090	160	0.406	357	4.964
	60	200	160	2.69	0.943	200	169	1.94	1.534	149	0.521	242	7.055
	80	200	172	1.81	0.985	200	178	1.11	1.558	123	0.589	389	9.393
	100	200	172	2.21	1.104	200	177	1.97	1.817	96	0.561	253	11.483
1.4	20	200	152	5.43	0.420	200	155	4.28	0.732	130	0.170	342	2.667
	40	200	168	2.54	0.569	200	171	2.40	0.943	112	0.269	392	4.917
	60	200	159	3.20	0.952	200	167	2.23	1.581	156	0.559	364	6.753
	80	200	171	1.95	0.882	200	179	1.25	1.420	117	0.556	335	8.779
	100	200	172	2.31	1.088	200	177	1.53	1.804	110	0.605	337	11.031
1.3	20	200	159	4.79	0.352	200	168	3.01	0.593	163	0.210	270	2.604
	40	200	173	2.71	0.432	200	180	1.58	0.682	119	0.286	201	4.247
	60	200	171	2.93	0.669	200	177	2.62	1.062	115	0.399	142	6.167
	80	200	170	2.57	0.818	200	175	2.10	1.349	79	0.353	577	8.316
	100	200	184	0.76	0.757	200	186	0.60	1.138	86	0.472	184	9.987
1.2	20	200	164	4.19	0.349	200	169	3.59	0.549	132	0.182	189	2.549
	40	200	167	3.39	0.465	200	177	2.14	0.764	135	0.301	366	4.331
	60	200	170	2.93	0.645	200	175	2.34	1.077	102	0.334	301	6.276
	80	200	173	2.04	0.783	200	176	1.87	1.303	81	0.346	173	8.325
	100	200	178	2.10	0.845	200	181	1.03	1.346	83	0.435	267	10.026
1.1	20	199	180	1.96	0.204	199	182	1.90	0.318	69	0.102	69	2.502
	40	199	178	2.07	0.315	200	182	1.75	0.517	72	0.157	328	4.161
	60	200	184	1.85	0.382	200	188	1.21	0.596	72	0.243	52	6.127
	80	200	185	1.56	0.430	200	188	1.34	0.694	62	0.259	43	7.515
	100	200	186	1.57	0.464	200	191	0.77	0.737	68	0.328	181	9.421

track the number of requests that have been optimally solved (column #*Opt*). The sub-columns *Iter* and *ET* contain the average number of iterations and the average execution time required to produce these optimal solutions. The last major column *Non-Opt* records information on those test cases for which no optimal solutions were found. Sub-column *Iter* records the iteration at which the best feasible solution was encountered.

From the numerical results, we have the following observations:

(1) For the case that χ has a tight value, it is guaranteed to find a feasible solution with less iterations or fewer ants. According to the following three sets of experimental results in χ=1.1 of Table 4, (i) #*Fea*=190 in b=20 and at the end of 1000 iterations, (ii) #*Fea*=200 in b=100 and at the end of 1000 iterations, and (iii) #*Fea*=198 in b=20 and at the end of 2000 iterations, the first and the second sets of results indicate that more ants can benefit to find feasible solutions. This is due to wider and diversified explorations within the solution space. Moreover, the second and the third sets of results demonstrate that execution with more cycles will have a higher probability of finding feasible solutions.

(2) When a request with a tight delay bound which is close to the minimum transmission delay, it seems to take less execution time because the ants were soon trapped and because a tight delay bound diminishes the number of viable wavelength links. It is thus less possible to compose feasible solutions. This reasoning is evinced in the numerical results. For example, for χ=1.1 and =1.5 in Table 5, we have #*Fea*=196 and #*Fea*=200, and *ET*=0.657 s and 1.483 s at the end of 1000 iterations for b=60.

(3) According to the comparisons from Tables 2 to 5, the execution time of the ACO algorithm is not sensitive to the change of the number of switches and the tightness of delay bound; but the time required by the ILP formulation highly depends on the change of the two features. For example, the *ET* values of ACO for χ=1.1, n=40, 50, and 60 are less than 1 s, but the corresponding *ET* values of ILP are more than 32, 395, 1380 s. This demonstrates the robustness and superiority of the ACO algorithm for the DRWA-DC problem.

(4) Although a larger number of iterations and ants deployed in ACO can reduce the communication cost of feasible solutions, the long execution time may be inefficient. The maximum average numbers of iterations to optimally solve optimally and non-optimally requests are 124 and 318 for n=40, 123, and 440 for n=50, and 169 and 420 for n=60. Therefore, the stopping criterion adopts the combination of that a given number of consecutive iterations within which no improvement on solutions is attained and a given limited number of iterations,

Table 4
Results of 200 requests routing in 50 nodes (n=50).

χ	b	1000 iterations				2000 iterations				Opt		Non-opt	
		#Fea	#Opt	Dev (%)	ET	#Fea	#Opt	Dev (%)	ET	Iter	ET	Iter	ET
3.0	20	200	169	0.98	0.614	200	174	0.61	1.010	139	0.367	832	5.313
	40	200	172	0.73	0.922	200	181	0.46	1.455	122	0.585	572	9.743
	60	200	178	0.49	1.204	200	185	0.31	1.868	123	0.883	739	14.014
	80	200	181	0.46	1.408	200	185	0.30	2.223	99	0.979	694	17.562
	100	200	181	0.44	1.618	200	185	0.26	2.543	80	0.907	835	22.724
2.0	20	200	152	3.78	0.621	200	156	2.21	1.089	129	0.256	706	4.045
	30	200	156	2.21	1.017	200	165	1.28	1.697	166	0.609	747	6.825
	60	200	164	1.50	1.342	200	174	0.79	2.009	168	0.880	515	9.561
	80	200	167	1.89	1.516	200	176	0.87	2.397	145	0.958	625	12.951
	100	200	170	0.94	1.762	200	175	0.80	2.825	109	0.907	378	16.248
1.5	20	200	143	8.61	0.618	200	149	6.71	1.084	142	0.247	506	3.527
	40	200	151	5.50	0.948	200	158	4.67	1.655	143	0.418	367	6.308
	60	200	154	3.88	1.160	200	161	2.95	2.066	120	0.492	535	8.566
	80	200	152	3.82	1.665	200	159	2.69	2.875	123	0.740	461	11.154
	100	200	155	2.98	1.865	200	161	2.48	3.271	108	0.785	489	13.532
1.4	20	200	142	8.71	0.587	200	153	7.02	1.013	171	0.286	274	3.379
	40	200	156	6.11	0.843	200	161	4.11	1.457	123	0.369	521	5.950
	60	200	162	4.98	1.024	200	170	3.56	1.732	144	0.541	427	8.479
	80	200	165	4.27	1.362	200	172	3.03	2.183	145	0.788	422	10.752
	100	200	165	3.51	1.379	200	170	2.44	2.452	85	0.574	411	13.091
1.3	20	198	155	6.75	0.478	199	164	5.80	0.826	161	0.285	231	3.287
	40	200	158	7.11	0.751	200	166	5.24	1.291	140	0.393	519	5.675
	60	199	162	5.16	0.960	199	172	3.87	1.649	157	0.648	322	7.800
	80	200	170	3.74	1.004	200	175	2.67	1.688	112	0.545	299	9.692
	100	200	164	4.00	1.274	200	169	2.75	2.265	90	0.510	435	11.830
1.2	20	197	154	6.80	0.432	199	165	5.63	0.739	163	0.259	269	3.003
	40	200	161	5.82	0.622	200	171	4.72	1.018	137	0.328	304	5.084
	60	199	166	5.74	0.772	200	173	4.34	1.333	106	0.369	380	7.514
	80	200	169	5.11	1.042	200	173	4.66	1.743	111	0.512	294	9.625
	100	200	171	4.23	1.109	200	174	3.76	1.927	77	0.450	188	11.813
1.1	20	190	169	4.37	0.347	198	178	4.61	0.547	150	0.247	370	2.972
	40	198	170	4.56	0.488	199	176	3.68	0.830	106	0.279	272	4.878
	60	198	182	2.43	0.545	198	187	1.52	0.847	102	0.426	199	6.908
	80	199	181	2.03	0.660	199	183	1.86	1.074	70	0.378	61	8.571
	100	200	185	2.73	0.620	200	186	2.39	0.978	53	0.299	188	10.003

which may be more reasonable. The comparisons about the number of iterations will be discussed in following section.

4.3. Comparisons of iterations

This part is dedicated to investigating the number of consecutive iterations within which no improvement is attained on solution values. Average experimental results of *Dev*, *ET*, *#Fea*, and *#Opt* of different χ values (χ=3.0, 2.0, 1.5, 1.4, 1.3, 1.2, and 1.1) are shown in Figs. 2–7 for different numbers of consecutive iterations (*Iter*=200, 400, 600, 800, and 1000) and different networks (n=40, 50, and 60). According to the experimental results, the type of stopping criterion can provide the performance with less execution time and approximated deviation in average. The number of consecutive iterations could be determined by the response time and the number of ants. Nevertheless, deviation and execution time seem to be the reasonable factors. From different criteria, we make several observations:

(1) From the experimental results in Figs. 2–4, the value of *Dev* decreases steadily for the increase of the number of ants and the increase of the number of iterations. For example, in Fig. 2, the average values of *Dev* are 7.38, 5.14, 4.52, 3.93, and 3.57% for 200, 400, 600, 800, 1000 iterations in 20 ants (b=20), and are 4.82, 4.19, 3.84, 2.77, and 2.93% for 40, 60, 80, 100, and 110 ants in 200 iterations. More ants collaborate through a longer execution course would accumulate and share more knowledge (in the differentiation of pheromone densities over edges) through extensive explorations. Nevertheless, it is not clear which factor's increase has impacts on the decrease the *Dev* values.

(2) According to the experimental results in Fig. 5, the elapsed execution time is proportional to the numbers of ants and iterations. This is due to the fact that the algorithmic steps required in the ACO algorithm are proportional to the ant population and the number of cycles. Besides, the ACO algorithm needed a larger number of consecutive iterations and fewer ants seem to provide lower deviation and to take longer run time than the ACO algorithms that used a smaller number of consecutive iterations and more ants. For example, in Figs. 4 and 5 (n=60), the values of *ET* and *Dev* are 3.622 s and 3.84% in b=40 and 1000 iterations, and 2.165 s and 4.85% in b=130 and 200 iterations.

(3) For the approximate elapsed execution time, it is more likely for the ACO algorithm needed a larger number of consecutive iterations and fewer ants to construct feasible solutions than the ACO algorithms using less consecutive iterations and more ants. Nevertheless, for the opportunity of attaining

Table 5
Results of 200 requests routing in 60 nodes (n=60).

χ	b	1000 iterations				2000 iterations				Opt		Non-opt	
		#Fea	*#Opt*	*Dev* (%)	*ET*	*#Fea*	*#Opt*	*Dev* (%)	*ET*	*Iter*	*ET*	*Iter*	*ET*
3.0	20	200	152	1.40	1.147	200	159	1.04	1.847	220	0.681	731	6.371
	40	200	156	0.93	1.793	200	168	0.62	2.870	236	1.262	597	11.313
	60	200	158	0.92	2.288	200	168	0.64	3.751	168	1.373	592	16.237
	80	200	168	1.11	2.550	200	177	0.37	4.020	161	1.704	621	21.847
	100	200	174	0.47	2.643	200	181	0.32	4.098	133	1.768	603	26.297
2.0	20	200	133	4.83	1.015	200	144	3.12	1.768	237	0.597	668	4.778
	30	200	141	3.65	1.473	200	150	1.94	2.579	187	0.802	500	7.910
	60	200	146	2.51	2.018	200	157	1.92	3.370	194	1.190	411	11.331
	80	200	149	2.61	2.445	200	159	1.90	4.172	185	1.479	475	14.618
	100	200	150	1.90	2.961	200	164	1.52	4.781	213	2.058	382	17.188
1.5	20	200	140	7.15	0.869	200	151	5.66	1.416	223	0.491	465	4.268
	40	200	149	6.18	1.246	200	159	4.77	2.020	210	0.730	468	7.025
	60	200	158	4.21	1.483	200	164	3.35	2.464	165	0.831	498	9.905
	80	200	158	3.52	1.803	200	169	2.16	2.872	177	1.140	441	12.311
	100	200	163	2.78	1.958	200	172	1.72	3.085	179	1.273	380	14.214
1.4	20	200	139	7.61	0.784	200	152	5.95	1.298	252	0.500	315	3.828
	40	200	150	6.33	1.081	200	160	3.37	1.801	199	0.639	522	6.445
	60	200	153	4.66	1.506	200	161	4.21	2.460	188	0.841	302	9.144
	80	200	165	3.51	1.473	200	174	2.27	2.323	173	0.981	377	11.307
	100	200	156	3.84	2.065	200	171	1.98	3.367	210	1.498	789	14.388
1.3	20	199	143	6.40	0.550	200	155	4.31	0.927	187	0.297	330	3.098
	40	200	148	6.12	0.718	200	158	4.18	1.221	154	0.352	252	4.488
	60	200	159	4.59	0.848	200	164	3.86	1.453	130	0.418	376	6.167
	80	200	165	2.74	1.073	200	172	2.05	1.657	156	0.640	237	7.907
	100	200	172	3.03	1.083	200	178	2.21	1.682	143	0.704	277	9.594
1.2	20	199	146	6.61	0.458	200	156	5.01	0.773	163	0.227	336	2.711
	40	199	158	5.40	0.636	200	167	2.81	1.020	151	0.352	570	4.402
	60	200	160	4.18	0.822	200	167	2.74	1.381	142	0.447	367	6.111
	80	200	162	3.69	0.975	200	165	3.11	1.703	98	0.381	340	7.936
	100	200	165	3.79	1.135	200	169	2.59	1.951	112	0.568	425	9.493
1.1	20	193	167	2.77	0.366	196	170	2.74	0.595	127	0.251	225	2.548
	40	196	170	2.77	0.506	198	174	2.39	0.827	113	0.317	258	4.239
	60	196	170	2.74	0.657	197	177	1.96	1.076	114	0.469	196	5.748
	80	198	178	2.31	0.650	199	181	2.08	1.030	77	0.360	262	7.415
	100	198	179	1.65	0.763	199	189	1.02	1.146	132	0.693	106	8.936

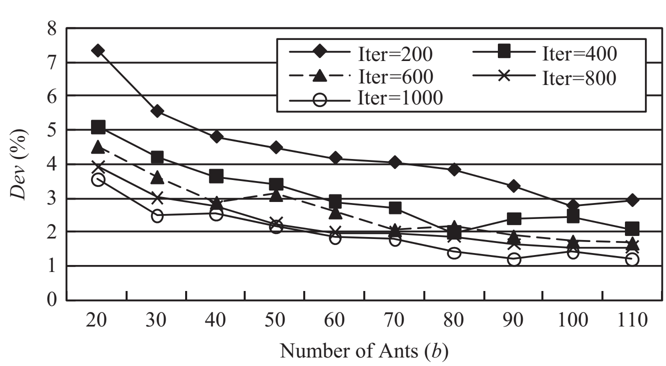

Fig. 2. The values of *Dev* for different numbers of ants in 40 nodes (n=40).

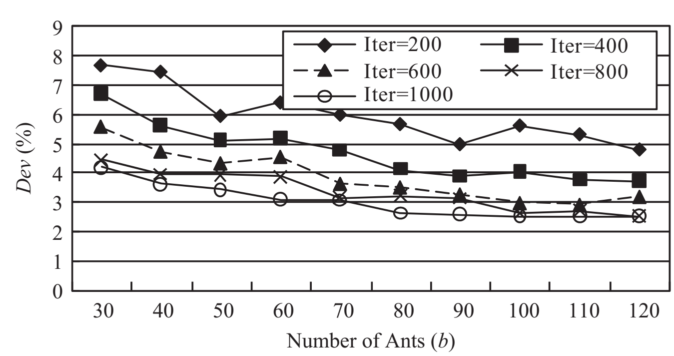

Fig. 3. The values of *Dev* for different numbers of ants in 50 nodes (n=50).

optimal solutions, the situation is reversed. For example, for the results of the values of *#Fea* shown in Fig. 6 and *Opt* shown in Fig. 7 (n=60), ET=2.165, *#Fea*=198.7, and *#Opt*=150.6 for 200 iterations in b=130, and ET=2.171, *#Fea*=199.0, and *#Opt*=148.9 for 400 iterations in b=60. Nevertheless, the phenomenon is inconspicuous.

(4) Although it is hard to decide the most appropriate ant population and the number of iterations, the colony with a greater number of ants seem to let the ACO algorithm find feasible solutions in a more efficient way. This could be attributed to the fact that the increase of ant populations can better facilitate the mechanism of information or knowledge sharing. To route the requests with less deviation and higher success probability, we suggest that the ant population may be set as the number of nodes in the network plus 20, and that the value of consecutive iterations is set as large as possible.

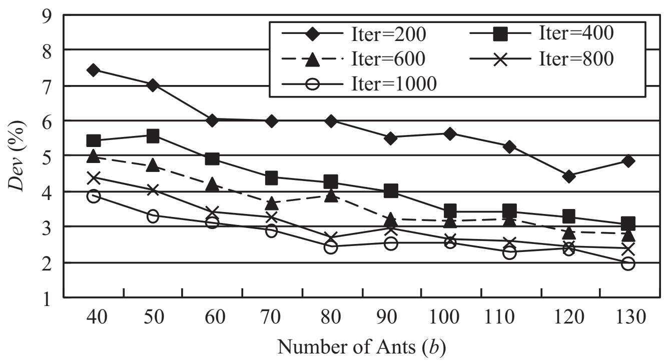

Fig. 4. The values of *Dev* for different numbers of ants in 60 nodes (n=60).

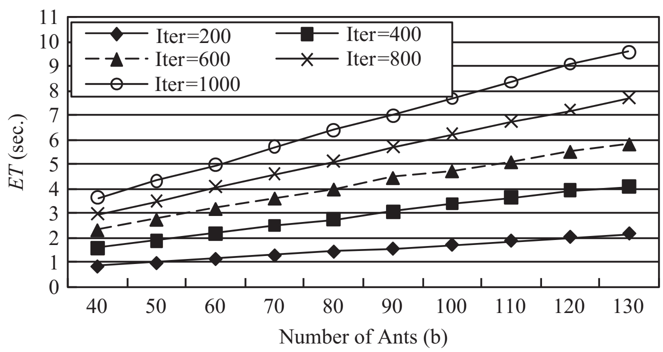

Fig. 5. *ET* for different numbers of ants in 60 nodes (n=60).

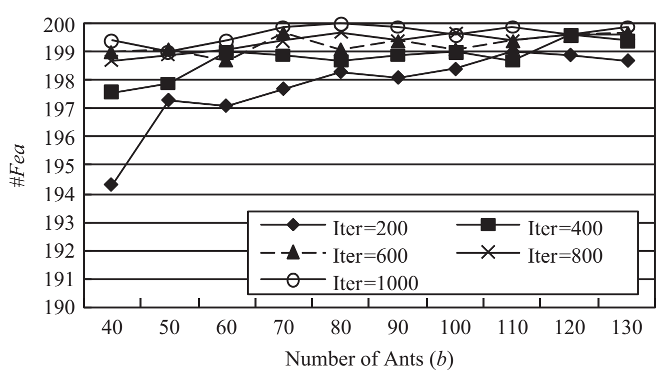

Fig. 6. #*Fea* for different numbers of ants in 60 nodes (n=60).

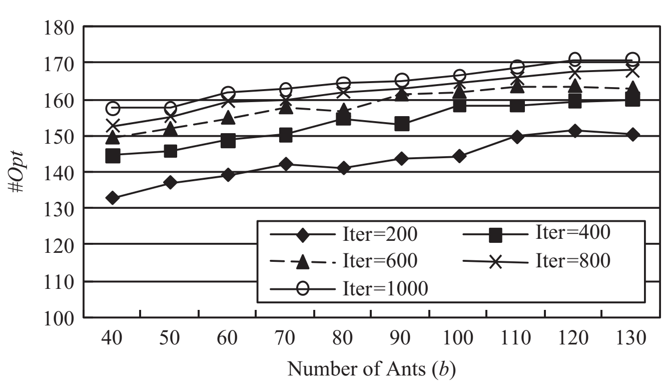

Fig. 7. #*Opt* for different numbers of ants in 60 nodes (n=60).

5. Conclusions

In this paper, a meta-heuristic scheme based upon ant colony optimization has been proposed to compose approximate solutions to the DRWA-DC problem, which is already known to be computationally intractable. Some heuristics for the SRWA problem and the DRWA problem have been developed in the literature, but few of them have applied the ACO approach or have addressed the issue concerning delay bounds. In this study, we have designed and implemented an ACO approach for solving the DRWA-DC problem. To adjust the ACO approach to meet the specific characteristics of the studied problem, a wavelength-link-based graph is constructed for the ants to traverse on. The effectiveness and robustness of the ACO approach have been examined by extensive experiments. We have also implemented the ILP formulation as a baseline to study the performance of the proposed ACO approach.

The experimental results have clearly evinced that our proposed ACO algorithm can find approximate solutions with average deviations of less than 4% from the optimal ones with an average elapsed execution time only about 0.1% of that required by an ILP formulation. Moreover, the ACO algorithm still works well in solving the DRWA-DC problem for large-scale networks, for which the ILP formulation fails to provide optimal solutions in a reasonable time.

The purpose of this paper is not to address the superiority the ACO over other meta-heuristic in solving the RWA problem. Our focus is set on addressing the applicability as well as the capability of the ACO algorithm in dealing with the DRWA-DC problem. Our study has not only extended the application areas of the ACO approach but also suggested a new viable method for coping with the complex optimization problems arising from the WDM domain. For further research, it is of potential interest to apply the ACO approach to solve the static RWA-DC problem or the logical network topology design problems. Besides, the multicast routing and wavelength assignment may be another interesting research direction.

References

Chen, M.T., Tseng, S.S., 2003. Multicast routing and wavelength assignment with delay constraint in WDM networks with heterogeneous capabilities—new ILP. In: Proceedings of the International Symposium on Communications (ISCOM), Tao-Yuan, Taiwan.

Chlamtac, I., Ganz, A., Karmi, G., 1992. Light-path communications: approach to high bandwidth optical WAN. IEEE Transactions on Communication 40, 1171–1182.

Dijstra, E.W., 1959. Anode on two problems in connexion with graph. Numerische Mathematik 1, 269–271.

Dorigo, M., Maniezzo, V., Colorni, A., 1991. Positive feedback as a search strategy. Technical Report, 91-016, Politecnico di Milano, IT.

Dorigo, M., Gambardella, L.M., 1997. Ant colonies for the traveling salesman problem. BioSystems 43, 73–81.

Garlick, R.M., Barr, R.S., 2002. Dynamic wavelength routing in WDM networks via ant colony optimization. In: Proceedings of the Third International Workshop on Ant Algorithms, Brussels, Belgium, pp. 250–255.

Green, P.E., 1992. Fiber-optic Networks, Cambridge, MA. Prentice-Hall.

Karasan, E., Ayanoglu, E., 1998. Performance of WDM transport networks. IEEE Journal of Selected Areas in Communications 16, 1081–1096.

Kavian, Y.S., Rashvand, H.F., Ren, W., Leeson, M.S., Hines, E.L., Naderi, M., 2007. RWA problem for designing DWDM networks—delay against capacity optimization. Electronics Letters 2 (43), 892–893.

Krishnaswamy, R.M., Sivarajan, K.N., 2001. Algorithms for routing and wavelength assignment based on solutions of LP-relaxations. IEEE Communications Letters 5/10, 435–437.

Kwang, M.S., Weng, H.S., 2003. Ant colony optimization for routing and load-balancing: survey and new directions. IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Human 33/5, 560–572.

Lin, B.M.T., Lu, C.Y., Shyu, S.J., Tsai, C.Y., 2008. Development of new features of ant colony optimization for flowshop scheduling. International Journal of Production Economics 112/2, 742–755.

Lowe, E., 1998. Current European WDM development trends. IEEE Communications Magazine 36/2, 46–50.

McMullen, P.R., Tarasewich, P., 2006. Multi-objective assembly line balancing via a modified ant colony optimization technique. International Journal of Production Research 44, 27–42.

Ngo, S.H., Jiang, X., Horiguchi, S., 2006. An ant-based approach for dynamic RWA in optical WDM networks. Photonic Network Communications 11, 39–48.

Qin, H., Zhang, S., Liu, Z., 2003. Dynamic routing and wavelength assignment for limited-rang wavelength conversion. IEEE Communications Letters 7, 136–138.

Ramamurthy, B., Mukherjee, B., 1998. Wavelength conversion in WDM networking. IEEE Journal of Selected Areas in Communications 16, 1061–1073.

Sabuncuoglu, I., Erel, E., Alp, A., 2009. Ant colony optimization for the single model U-type assembly line balancing problem. International Journal of Production Economics 120/2, 287–300.

Saradhi, C.V., Gurusamy, M., Zhou, L., 2007. Distributed network control for establishing reliability-constrained least-cost lightpaths in WDM mesh networks. Computer Communications 30, 1546–1561.

Shen, G., Bose, S.K., Cheng, T.H., Lu, C., Chai, T.Y., 2001. Efficient Heuristic algorithms for light-path routing and wavelength assignment in WDM networks under dynamically varying loads. Computer Communications 24, 364–373.

Shyu, S.J., Yin, P.Y., Lin, B.M.T., Haouari, M., 2003. Ant-tree: an ant colony system for the generalized minimum spanning tree problem. Journal of Experimental and Theoretical Artificial Intelligence 15, 103–112.

Shyu, S.J., Lin, B.M.T., Yin, P.Y., 2004a. Application of ant colony optimization for no-wait flowshop scheduling to minimize the total completion time. Computers and Industrial Engineering 47/2–3, 181–193.

Shyu, S.J., Yin, P.Y., Lin, B.M.T., 2004b. An ant colony optimization algorithm for the minimum weight vertex cover problem. Annals of Operations Research 13, 283–304.

Silva, C.A., Sousa, J.M.C., Runkler, T.A., da Costa, J.M.G.S., 2006. Distributed optimisation of a logistic system and its suppliers using ant colonies. International Journal of Systems Science 37/8, 503–512.

Sun, Z.G., Teng, H.F., 2003. Optimal layout design of a satellite module. Engineering Optimization 35, 513–529.

Udomsakdigool, A., Kachitvichyanukul, V., 2008. Multiple colony ant algorithm for job-shop scheduling problem. International Journal of Production Research 46, 4155–4175.

Varela, G.N., Sinclair, M.C., 1999. Ant-colony optimization for virtual wavelength-path routing and wavelength allocation. In: Proceedings of the Congress on Evolutionary Computation (CEC'99), Washington, DC, USA, pp. 1809–1816.

Wang, D., Ip, W.H., 2005. Ant search based control optimisation strategy for a class of chaotic system. International Journal of Systems Science 36, 951–959.

Waxman, B.M., 1988. Routing of multipoint connections. IEEE Journal of Selected Areas in Communications 6, 1617–1622.