

Ant Colony Optimization for Distributed Routing Path Optimization in Optical Burst-Switched Networks

João Pedro^{1,2}, João Pires², and Joao Paulo Carvalho³

¹ Nokia Siemens Networks Portugal S.A., R. Irmãos Siemens 1, 2720-093 Amadora, Portugal

² Instituto de Telecomunicações, Instituto Superior Técnico, Av. Rovisco Pais 1, 1049-001 Lisboa, Portugal

³ INESC-id, Instituto Superior Técnico, R. Alves Redol 9, 1000-029 Lisboa, Portugal

Email: joao.pedro@nsn.com, jpires@lx.it.pt, joao.carvalho@inesc-id.pt

Abstract—This work describes a distributed framework for routing path optimization in Optical Burst-Switched (OBS) networks that loosely mimics the foraging behaviour of ants observed in nature, which in the past has originated the Ant Colony Optimization (ACO) metaheuristic. The framework consists of additional data structures stored at the nodes and of special control packets that traverse the network, estimate the goodness of their paths and update accordingly the data structures of the nodes. The performance of the framework, which has been implemented on an event-driven OBS network simulator, is evaluated on several network topologies and compared with that obtained with centralized routing path optimization. The simulation results show that the distributed routing path selection framework significantly improves the performance of OBS networks by reducing data loss and that it attains a performance comparable to that of the centralized algorithm. The results also suggest that the framework is robust to changes in its parameters.

Keywords—Ant colony optimization, optical burst switching, routing path optimization, swarm intelligence.

1 Introduction

The foraging behaviour of some ant species has inspired the ant colony optimization metaheuristic [1], which has become one of the most successful swarm intelligence methods for problem solving [2]. Ant colonies are distributed systems that take advantage of their structured social organization to accomplish complex tasks while relying only on very simple individuals. This property, where a colony is able to perform tasks whose complexity far exceeds that of an individual, has made ant colonies a source of inspiration to develop artificial distributed systems and algorithms [3].

It has been shown that ACO algorithms can efficiently solve routing problems in some types of telecommunication networks, namely in circuit-switched [4] and packet-switched [5] networks. Recently, ACO algorithms were also devised for the routing and wavelength assignment problem that arises in Wavelength Division Multiplexing (WDM) optical networks [6], [7].

Circuit-switched WDM optical networks are worldwide used as backbone and metropolitan networks, due to their high capacity and low transmission losses. However, their coarse granularity limits their effectiveness to support bursty Internet Protocol (IP) packet traffic. Research efforts have been directed to finer-grained optical networking paradigms, such as optical burst switching [8]. At the edge nodes of OBS networks, multiple IP packets are assembled into bursts

of data, which are then transmitted towards their egress nodes. A one-way resource reservation mechanism without acknowledgement of successful reservation in the burst path is used to allocate wavelength channels to the upcoming data bursts. Hence, there is the possibility that two or more bursts contend for the same wavelength channel at the core nodes, which is further augmented by the lack of efficient optical buffers (limiting the capability to delay data bursts). Thus, contention is a major issue in OBS networks and minimizing it is of paramount importance. One approach to mitigate contention consists of optimizing the routing paths of data bursts as to balance the traffic load across the network links.

This paper describes a distributed framework for routing path optimization in OBS networks inspired on ACO and assesses its performance using network simulation. The simulation results show that this framework can efficiently reduce contention, thus improving network performance, without requiring a fine tuning of its main parameters.

The remainder of the paper is organized as follows. Section 2 describes the ant foraging behaviour observed in nature and its utilization for network routing optimization, whereas section 3 introduces the OBS network architecture and the relevance of optimizing the paths used to route data bursts. The proposed distributed routing path optimization framework for OBS networks, embedding collective intelligence and problem solving capabilities observed in colonies of ants is described in section 4. The performance of the proposed framework is evaluated through network simulation and compared to that obtained with shortest path routing and a centralized routing path optimization algorithm in section 5. Finally, section 6 presents the conclusions.

2 Ant colony optimization and its applications

2.1 Ants in Nature

Individual ants are very simple insects whose behaviour appears to have a large random component. Despite their individual simplicity, when acting collectively they are able to execute complicated tasks with significant consistency and reliability. For instance, some ant species can collectively cooperate in regulating the nest temperature, raiding particular areas for food, building and protecting the nest, carrying large items, preferentially exploiting the richest available food source and, more related to this work, finding the shortest routes from the nest to a food source [4]. These

relatively complex tasks seem to emerge from interactions between large numbers of ants and their environment. In some cases, individual ants coordinate their activities using a principle known as *stigmergy* [1], whose main characteristics are: (i) indirect and non-symbolic form of communication mediated by the environment, that is, ants exchange information by modifying their environment; (ii) stigmergic information is local, which means that it can only be accessed by ants that visit the immediate vicinity of the place where it was released.

The communication between individual ants is based on the use of specific chemicals, called pheromones. Particularly important for the social life of some ant species is the *trail pheromone*, which is a specific type of pheromone they use for marking paths on the ground. While walking between food sources and the nest, ants deposit pheromones on the ground, forming a pheromone trail. Subsequent ants sense the pheromone and tend to choose, probabilistically, paths with a stronger pheromone concentration, further reinforcing it. After some time, ants converge to use a single shortest path. A compendium of seminal works on the pheromone trail-laying and trail-following behaviour of some ant species can be found in [3].

2.2 Ant Colony Optimization for Network Routing

The basic idea underlying ant colony-based algorithms and systems is to use a form of *artificial stigmergy* to coordinate the activities of *artificial agents*. The majority of ACO applications have been for solving \mathcal{NP} -hard problems, for which the best known algorithms that guarantee an optimal solution have an exponential time worst case complexity. In some of these problems, ACO algorithms have been shown to determine high-quality, although not guaranteed to be optimal, solutions in relatively short time.

The routing problems in telecommunication networks are particularly interesting for ACO, because the intrinsically distributed nature of ACO can fit well with them. However, these problems pose additional challenges, because the routing algorithm should also be able to react rapidly to changing network and traffic conditions and to maintain exploration capabilities so that it can effectively evaluate alternative paths which, in view of the problem dynamics, can become the best ones at some point in time [1].

The different ACO algorithms for network routing have in common the fact that pheromone tables are stored at the network nodes and artificial agents, typically in the form of control packets, are employed to collect node/link state information and update the pheromone tables. ACO was first applied to network routing in circuit-switched networks, like the Plain Old Telephone Service (POTS), in [3]. The main purpose of Ant-Based Control (ABC) is to relieve congestion on the network by preferably routing calls (circuits) via parts of the network with larger spare capacity, consequently reducing call blocking probability. Later, ACO was applied to routing in packet-switched networks, such as IP networks, in [5]. These networks use store-and-forward nodes, which contain buffers to store the incoming packets and delay them until there is free capacity on the preferred output link. With

AntNet [5], an artificial ant is launched at regular intervals of time from a network node towards another node to discover a low-cost path between the nodes and to investigate the load status of the network. The selection of the next node by an ant is made by assigning to the neighbouring nodes a probability of being selected that depends not only on the correspondent pheromone value but also on the occupancy of the queue associated to the link between the current node and the neighbouring node. Hence, the chances of selecting a neighbouring node increase with its pheromone value but decrease with the queue waiting time associated to it.

ACO has also found application on routing in optical WDM networks, both in Optical Circuit-Switched (OCS) [6], [7] and Optical Packet-Switched (OPS) networks [9]. AntNet was adapted in [9] for load balancing in OPS networks. The nodes of these networks use Fibre Delay Line (FDL) buffers, which have a very limited contention resolution capability, when compared to electronic buffers. The proposal modifies the solution construction phase of the original AntNet implementation [5] using a suitable expression for computing the buffer occupancy, since FDL buffers behave differently from electronic buffers.

Despite the recent research activity aiming to use ACO for routing in optical WDM networks, both in OCS and OPS, to the best of the author's knowledge ACO has not yet been adapted to the case of OBS networks.

3 Optical burst-switched networks

In current optical transport networks, circuits are established between nodes during long periods of time (weeks, months) using wavelength channels with a capacity of several Gbit/s each. However, the dominant IP packet traffic carried over these networks significantly fluctuates over relatively small time scales. Hence, current circuit-switched optical networks are inefficient to support this type of traffic due to both their coarse granularity and slow circuit setup time. OPS networks would provide the best adaptation between the IP traffic and the optical network resources used, but they cannot be implemented with state-of-the-art technology, namely due to the already referred lack of efficient optical buffers. OBS networks have attracted considerable interest because their switching granularity and optical technology complexity are in between those of OCS and OPS [10].

3.1 Network Architecture

At the ingress edge nodes of OBS networks, IP packets are assembled into large chunks of data, called bursts. Each data burst is transmitted using a wavelength channel and must be switched at the core nodes until it reaches the egress edge node, where it is disassembled and its packets delivered to the local IP network. Resource reservation for each burst is made using a control message, known as Burst Header Packet (BHP), sent ahead of the data burst on a separate wavelength channel. Each node along the routing path of the burst processes the BHP and configures its switching matrix to direct the upcoming data burst to an available wavelength channel on the appropriate output fibre link. The interested reader can find more information on OBS networks in [10].

3.2 Routing Path Optimization

In OBS networks, multiple data bursts, overlapping in time, may contend at a node for the same wavelengths of an output fibre link. Unresolved contention leads to dropping some of the data bursts, degrading network performance. Therefore, it is important to minimize the probability that the number of overlapping data bursts directed to a fibre link exceeds the number of wavelength channels. This can be achieved by optimizing the routing paths in order to balance the traffic load offered to the network links, reducing the traffic load on the most congested links at the expense of increasing it on the less congested ones.

Routing path optimization can either be centralized, when all the paths are computed at a central point of the network using global information of the offered traffic load [11], or distributed [12]. Although centralized strategies can reduce contention more efficiently, by exploiting global knowledge of the network state, distributed strategies are often preferred because they are more scalable and robust and faster to adapt the routing paths to changes in the traffic pattern.

4 Distributed Ant-inspired Burst Routing

The framework for distributed routing path optimization in OBS networks proposed in this work is based on principles of ACO. Although it inherits some concepts from previous ACO algorithms for network routing, such as AntNet and ABC, the proposed Distributed Ant-inspired Burst Routing (DABR) framework was specifically designed for bufferless OBS networks and incorporates functions that account for the particular characteristics of these networks.

Common to all applications of ACO for network routing, the DABR framework uses artificial ants, in the form of control packets, and data structures at the network nodes to support stigmergic communication between the artificial ants. The key features of DABR are:

- Forward ants carry a fictitious data burst reservation and, at each node, the instantaneous congestion of the output fibre links is evaluated based on the number of wavelengths available to transmit the fictitious burst.
- Backward ants update the pheromone tables using the congestion information collected by the forward ants as input to a loss performance model that estimates the burst blocking probability on the path traversed by the forward ant.
- In order to mitigate path stagnation, three mechanisms are used: the routing of forward ants employs both a minimum pheromone concentration per adjacent node (noise) and pheromone-heuristic control, whereas the backward ants use privileged pheromone laying [13].
- The nodes keep separate routing and pheromone tables because an additional path integrity mechanism is used to completely avoid circular path formation.

Consider an OBS network modelled as a directed graph $G = (V, E)$, where $N = |V|$ is the number of nodes and $L = |E|$ is the number of unidirectional fibre links. Assume each fibre link supports a set of W wavelengths, $\{\lambda_1, \lambda_2, \dots, \lambda_{W-1}, \lambda_W\}$. The following sub-sections describe the DABR framework.

4.1 Control Packets and Local Data Structures

In DABR, artificial ants are transmitted on the control channel as modified BHPs. Two types of artificial ants are used: Explorer Ant Packet (EAP) and Referee Ant Packet (RAP). The former ant is used to collect information on the resource availability along a given routing path and to update the pheromone tables, loosely mimicking the behaviour of real ants, whereas the latter one is used to avoid circular path formation. Both EAP and RAP have two modes of operation: forward (F), from the ingress to the egress node, and backward (B), in the reverse path. Two data structures are stored at each node: one pheromone table and one routing table. The pheromone table is used for routing the F-EAPs and it is updated in their return trips as B-EAPs. The routing table can only be updated by RAPs.

Unlike previous ACO routing algorithms, routing of artificial ants and data bursts in DABR is based not only on the egress node but also on the ingress node, providing an additional degree of freedom for load balancing at the expense of increasing the size of the tables. Let A_i denote the set of adjacent nodes of $i \in V$ (nodes connected to i by a fibre link) and τ_{ij}^{sd} denote the pheromone value associated to using node $j \in A_i$ to route at node i a burst generated at s and directed to d . The sum of the pheromone values related with the same ingress and egress node pair must equal one,

$$\sum_{j \in A_i} \tau_{ij}^{sd} = 1, \quad i, s, d \in V, s \neq d. \quad (1)$$

Let h_{ij} denote the number of links of the shortest path between i and j . The pheromone tables are initialized as to be slightly biased towards the shortest paths,

$$\tau_{ij}^{sd} = \begin{cases} \frac{1/(1+h_{jd})}{\sum_{k \in A_i} 1/(1+h_{kd})}, & j \in A_i, i \neq d, s \neq d \\ 0, & \text{otherwise} \end{cases}. \quad (2)$$

4.2 Routing of Forward Explorer Ants

Each time node s assembles a data burst directed to d , it generates with probability p_{ant} , where $0 < p_{\text{ant}} \leq 1$, an F-EAP that is routed from s to d to collect information on the resource availability of a particular path. The F-EAP carries a fictitious burst reservation request whose duration equals that of the burst that triggered the generation of the artificial ant and a list V_{EAP} with the nodes it has already visited.

At each node $i \in V$ visited by an F-EAP, the next node of its routing path is selected among the adjacent nodes not visited yet. In case $A_i \subseteq V_{\text{EAP}}$, the F-EAP is dropped to avoid looping. Otherwise, the adjacent node j is selected with a probability p_{ij}^{sd} that is the normalized sum of the pheromone value and a heuristic value η_{ij} that accounts for the resource availability on the fibre link between nodes i and j [5],

$$p_{ij}^{sd} = \begin{cases} \frac{\tau_{ij}^{sd}}{(1+\alpha) \sum_{k \in A_i, k \notin V_{\text{EAP}}} \tau_{ik}^{sd}} + \alpha \frac{\eta_{ij}}{(1+\alpha) \sum_{k \in A_i, k \notin V_{\text{EAP}}} \eta_{ik}}, & j \in A_i, j \notin V_{\text{EAP}} \\ 0, & \text{otherwise} \end{cases}. \quad (3)$$

The pheromone value is the result of pheromone laying by previous artificial ants and represents the long-term goodness of selecting the fibre link from i to j to route the F-EAP, whereas the heuristic value corresponds to the instantaneous goodness of selecting this fibre link. In order to compute η_{ij} , the wavelength availability of the fibre link ij is assessed by determining if the fictitious data burst could be scheduled on each of the W wavelengths of the fibre link. Let \hat{W}_{ij} denote the number of available wavelengths to schedule the data burst on this fibre link. The heuristic value η_{ij} is given by

$$\eta_{ij} = \hat{W}_{ij} / W. \quad (4)$$

The link state weight α determines the importance of the instantaneous resource availability of the fibre link over its long-term pheromone concentration.

The node selected j^* is added to the F-EAP, as well as the number of available wavelengths \hat{W}_{ij^*} . When it reaches the egress node, the artificial ant is switched to B-EAP.

4.3 Pheromone Table Update by Backward Explorer Ants

The B-EAP follows the reverse path of the F-EAP, updating the pheromone tables in each node. In an OBS network, the average burst blocking probability on a fibre link can be estimated with the Erlang-B formula, assuming an average offered traffic load of x and a Poisson burst arrival process,

$$\text{Erl}(x, W) = \left(x^W / W! \right) \cdot \left(\sum_{k=0}^W x^k / k! \right)^{-1}. \quad (5)$$

The wavelength availability \hat{W}_{ij} , collected by the F-EAP, is used to estimate the traffic load offered to the fibre link between i and j as $x = W - \hat{W}_{ij}$. Under the link independence assumption [14], the average burst blocking probability in the routing path between nodes s and d can be estimated by

$$B^{sd} = 1 - \prod_{k=1}^{|\mathcal{V}_{\text{EAP}}|-1} (1 - \hat{B}_{v_k v_{k+1}}), \quad (6)$$

where $\{v_1, v_2, \dots, v_k, \dots, v_{|\mathcal{V}_{\text{EAP}}|}\}$ denotes the ordered set of the nodes visited by the F-EAP and $\hat{B}_{v_k v_{k+1}}$ the average burst blocking probability in the fibre link between v_k and v_{k+1} . The goodness of a routing path is quantified in DABR as

$$q^{sd} = 1 / B^{sd}. \quad (7)$$

Each node i maintains the goodness of the best solution q_{best}^{sd} estimated by the previous Q artificial ants between s and d and the pheromone reinforcement value r is given by

$$r = \begin{cases} q^{sd} / q_{\text{best}}^{sd}, & q^{sd} < q_{\text{best}}^{sd} \\ 1, & \text{otherwise} \end{cases}. \quad (8)$$

In order to enhance the rewarding of good solutions (high values of r), while saturating the rewards for low values of r , the following squash function $s(x)$ is used [5],

$$s(x) = \left(1 + \exp \left(\frac{1}{r |\mathcal{V}_{\text{EAP}}|} \right) \right)^{-1}, \quad (9)$$

$$r \leftarrow \tau_{\max} \cdot s(r) / s(1), \quad (10)$$

where τ_{\max} is the maximum pheromone value that a single artificial ant can deposit. This parameter is used to regulate the impact of a single artificial ant on the pheromone tables.

The pheromone update has to ensure a minimum amount of pheromone τ_{\min} uniformly divided by the adjacent nodes,

$$\tau_{ik}^{sd} \geq \tau_{\min} / |A_i|, \quad k \in A_i, \quad (11)$$

and it also has to guarantee that equation (1) holds. Hence, the following expressions have been devised for updating the pheromone value associated to the adjacent node j the F-EAP has used and that associated to the remaining adjacent nodes,

$$\tau_{ij}^{sd} \leftarrow \tau_{ij}^{sd} + r \cdot \left(1 - \tau_{ij}^{sd} - \tau_{\min} \cdot (|A_i| - 1) / |A_i| \right), \quad (12)$$

$$\tau_{ik}^{sd} \leftarrow \tau_{ik}^{sd} - r \cdot \left(\tau_{ik}^{sd} - \tau_{\min} / |A_i| \right), \quad k \in A_i, k \neq j. \quad (13)$$

In case the update has modified the adjacent node that has the highest pheromone value, designated as the dominant adjacent node, a specific flag of the B-EAP is activated.

4.4 Routing Table Update and Circular Path Avoidance

In the initial implementation of DABR, data bursts were routed through the path obtained from the adjacent nodes with the largest pheromone concentration. However, it was found that circular paths were occasionally formed, which resulted in data bursts getting trapped on a loop. Although these paths are only temporary, the resulting communication disruption is not tolerable in a high capacity optical network. Hence, it is imperative to include in DABR a mechanism to avoid the formation of circular paths. The novel mechanism devised for this purpose separates the pheromone and routing tables, guaranteeing that the update of the routing paths never allows the formation of loops without introducing additional restrictions to the update of the pheromone tables.

Let v_i^{sd} denote the adjacent node of node i used for routing data bursts from node s to node d . The update of the routing path between s and d is triggered by the arrival at node s of a B-EAP with the flag that signals a new dominant adjacent node activated. As a result, node s generates a F-RAP directed to node d . This control packet includes a list to record the nodes it visits. At each node i the F-RAP visits, the dominant adjacent node j^* is determined, that is,

$$j^* = \arg \max_{j \in A_i} \{ \tau_{ij}^{sd} \}, \quad (14)$$

and compared with the nodes previously visited. In case node j^* has already been visited, a loop is detected and the F-RAP is discarded, keeping the routing path unchanged. Otherwise, the F-RAP adds the dominant adjacent node j^* to the list of nodes visited and moves to it. In case $j^* = d$, the new routing path is non-circular. Thus, the F-RAP is switched to B-RAP, follows the inverse path and, at each node i , the adjacent node used to route data bursts, v_i^{sd} , is updated to be the same as the node visited by the F-RAP immediately after i .

The routing of data bursts in DABR is determined by the routing tables of the nodes. In particular, when a BHP, preceding the correspondent data burst, arrives at node i , the node determines the next node of the data burst from v_i^{sd} .

5 Simulation Results

In OBS networks, the most relevant performance metric is the average burst blocking probability. The loss performance of OBS networks is evaluated using the network simulator of [15] modified to support DABR. All the simulations use the JET resource reservation mechanism [8], each fibre link has $W=32$ wavelength channels, each with a capacity $\mu=10$ Gb/s, the time to process one BHP or artificial packet is $100 \mu\text{s}$ and the switch fabric configuration time is $160 \mu\text{s}$. The burst size and interarrival time are exponentially distributed and the average burst size is 10 MB. The average offered traffic load normalized to the network capacity is given by

$$\Gamma = \frac{\sum_{s,d \in V} \gamma^{sd} \cdot h_{sd}}{L \cdot W \cdot \mu}, \quad (15)$$

where γ^{sd} is the average offered traffic load between nodes s and d . The performance evaluation is made with the network topologies of Fig. 1, assuming a uniform traffic pattern for EON and a non-uniform traffic pattern for COST 239. The average burst blocking probability and a 95% confidence interval on this value are obtained from 10 independent simulations with 5×10^6 data bursts each.

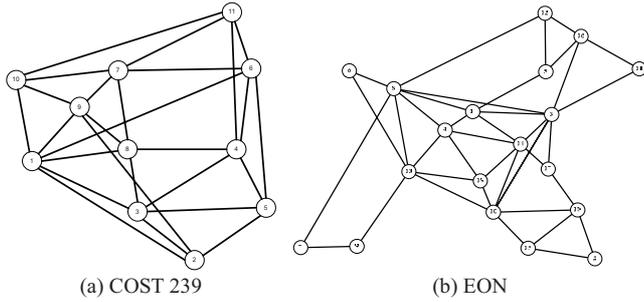
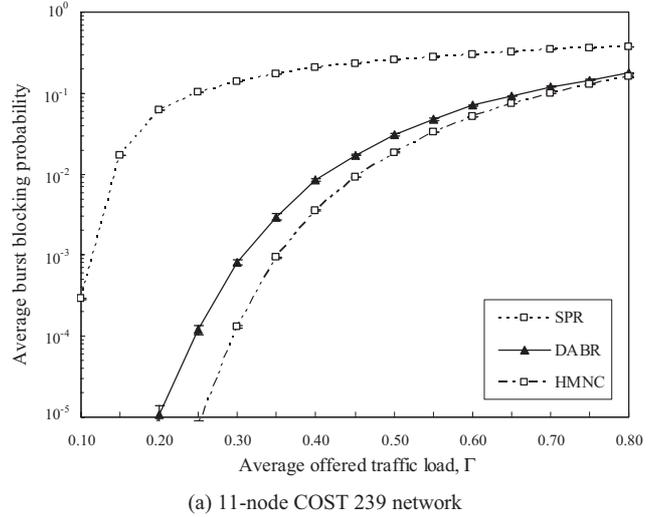


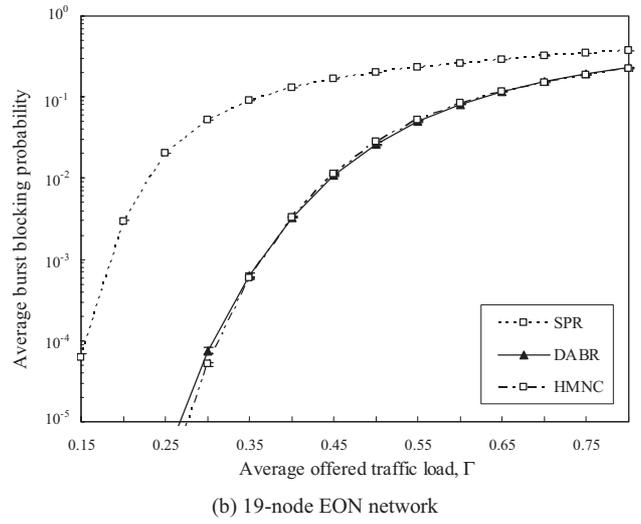
Figure 1: Network topologies.

Figure 2 plots the average burst blocking probability as a function of the average offered traffic load for the COST 239 and EON networks, respectively. The parameters used for DABR are $p_{ant}=0.05$, $\alpha=0.25$, $\tau_{min}=0.2$, $\tau_{max}=0.1$, and $Q=50$, aiming a compromise between performance and adaptability to changing conditions. For comparison purposes the plots also include the performance obtained with Shortest Path Routing (SPR) and the centralized HMNC algorithm of [11].

The simulation results show that the performance obtained with DABR lies between that of SPR and HMNC, although always closer to the latter. This is an expected outcome. On one hand, the simpler SPR does not optimize the traffic load distribution over the fiber links, which can significantly increase contention in some of the links. On the other hand, the HMNC algorithm is more effective because it exploits the global knowledge of accurate traffic statistics. However, in more dynamic traffic scenarios, where traffic statistics are less reliable, HMNC may become less effective than the proposed DABR. The simulation results also show that larger confidence intervals are obtained with DABR than that with SPR and HMNC. This is a consequence of the online modification of the routing paths observed when using DABR, while with SPR and HMNC the same set of routing paths is used during the entire simulation.



(a) 11-node COST 239 network



(b) 19-node EON network

Figure 2: Network performance of DABR, SPR and HMNC.

The performance impact of varying some of the parameters of DABR is assessed in the COST 239 network. In all cases, the parameter values given above are used with the exception of the parameter being varied. The average burst blocking probability as a function of the minimum pheromone value, maximum pheromone increment per EAP and size of sliding window used to record the best EAP solution are plotted in Figures 3, 4 and 5, respectively.

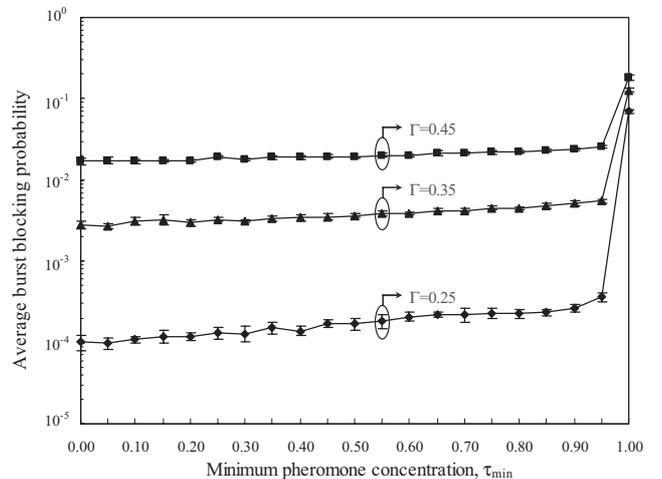


Figure 3: Performance impact of τ_{min} .

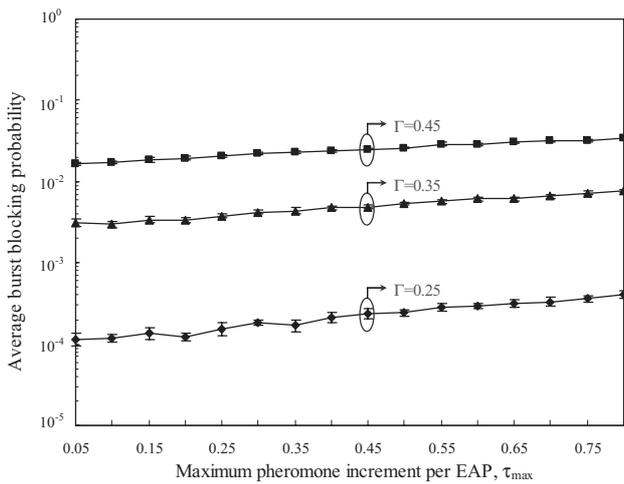


Figure 4: Performance impact of τ_{max} .

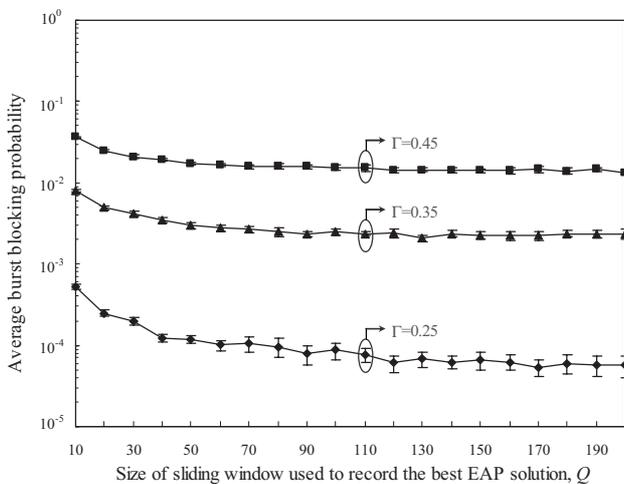


Figure 5: Performance impact of Q .

The results above consider three values of average offered traffic load in order to confirm that the behaviour observed is independent of the traffic load. According to the simulation results of Fig. 3, the loss performance slightly deteriorates as the minimum pheromone concentration on the adjacent nodes is increased. This is because the random component of routing the EAPs becomes larger, increasing the chances of modifications in the routing paths. In the limit case $\tau_{min}=1$, the network cannot optimize the set of routing paths.

From Fig. 4, it can be seen that the average burst blocking probability is slightly increased as the EAPs are allowed to deposit more pheromone in a single trip. This behaviour is attributed to more frequent modifications of the routing paths as a consequence of increased fluctuations of the pheromone values. A smaller pheromone increment makes the routing paths less sensitive to the goodness of the solution found by a single artificial ant, which means they are changed only when a significant number of EAPs have followed a given routing path and confirmed its superior quality.

As shown in Fig. 5, the use of a large Q can improve the network performance because it enhances the accuracy of the pheromone update process.

Overall, given the relatively small range of variation of the average burst blocking probability, the results suggest

that DABR is quite robust to changes in its main parameters. The results also suggest that a larger Q and a smaller τ_{min} and τ_{max} slightly improve loss performance. However, it should be stressed that the simulations consider a single traffic pattern (in terms of average offered traffic load), whereas in more dynamic traffic scenarios a very large Q and very small τ_{min} and τ_{max} should be avoided because they can slow down the convergence to a new set of optimized routing paths whenever significant changes in the traffic pattern take place.

6 Conclusions

This paper has proposed a novel distributed routing path optimization framework for OBS networks based on ACO concepts. Simulation results have shown that the proposed framework can significantly improve network performance without needing to fine tune its parameters.

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