

Cooperation through pheromone sharing in swarm routing

Vebjørn Kjeldsen

Master of Science in Communication Technology

Submission date: June 2007

Supervisor: Poul Einar Heegaard, ITEM

Problem Description

CEAS (Cross Entropy Ant System) is a distributed, robust and adaptive swarm intelligence system for path management in communication networks. The CEAS is performing adaptive multi-path load sharing and stochastic routing with fast restoration on link failures. Previous work have shown that CEAS is robust and efficient in solving complex optimisation problems like finding primary and backup paths and p-cycles in networks, and also finding paths in network with changes in topology and traffic load and patterns.

In CEAS there is a trade-off between management overhead (number of management packets) and path recovery times. In previous work the overhead is partly reduced by introduction of elitism, and self-tuning of the ant rate and conducting ant replication in the nodes. It has also been shown that the convergence rate will be reduced when different ants cooperate when they have (partly) overlapping targets. The cooperation through pheromones is the main focus in this assignment.

1. Investigate and propose pheromone sharing strategies (continuation of project)
2. Propose network test scenario and implement in simulator (ns2, DEMOS)
3. Identify relevant performance metrics for quantification of pheromone sharing
4. Setup and conduct series of simulations of at least one scenario
5. Evaluate pheromone sharing strategies (pro et contra)

Assignment given: 22. January 2007
Supervisor: Poul Einar Heegaard, ITEM

Abstract

Traditional routing protocols build routing tables that are optimized on one parameter only, this parameter is typically hop counts. With the introduction of new requirements, brought forth by a wide range of communication intensive, real-time multimedia applications, more sophisticated routing techniques are required. However, computing routes subject to different requirements and in environments with changing traffic patterns and network topologies, is often computationally excessive and the problems are frequently NP hard.

Swarm based algorithms, inspired by the foraging behavior of ants are candidates to solve such routing problems. To ensure system robustness and scalability, routing should be truly distributed and adaptive. The Cross Entropy Ants System (CEAS) is an adaptive, robust and distributed routing and management system based on swarm intelligence. CEAS is performing stochastic routing with fast restoration on link failures. Previous work has shown that CEAS is robust and efficient in solving complex optimization problems such as finding primary and backup paths or simple cyclic paths (p-cycles) in networks.

In all swarm systems there is a tradeoff between performance and management overhead (number of management packets). The focus in this work is on reducing the overhead in terms of management packets generated in CEAS. To achieve this, a new algorithm is proposed that applies pheromone sharing between sources going to identical destinations. Performance results from simulations show that the new CEAS system presented in this report outperforms the original CEAS in most scenarios.

PREFACE

This text is submitted as the concluding part of my Master of Science degree in Communication Technology at the Norwegian University of Science and Technology (NTNU). The work has been carried out at the Department of Telematics during the spring of 2007. My subject teacher has been Professor Poul E. Heegaard and my supervisor has been Otto J. Wittner, Post Doc at the Center of Quantifiable Quality of Service in Communication Systems, Centre of Excellence.

I would like to thank Poul E. Heegaard and Otto J. Wittner for their guidance and feedback through the whole thesis process.

Trondheim, June 25th, 2007

Vebjørn Kjeldsen

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

With the introduction of new routing requirements, brought forth by a wide range of communication intensive, real-time multimedia applications, more sophisticated routing techniques are required in today's communication networks. Performance requirements, Quality of Service (QoS), load balancing and scalability are thus becoming increasingly important factors concerning modern network routing. All paths between sources and destinations in a network should be chosen such that low latency, low loss and high throughput are achieved even in dynamic environments. Simultaneously an overall good utilization of network resources should be ensured. However, computing such routes is often computationally excessive and the problems are frequently NP hard. Several stochastic optimization techniques to path management have been proposed. Common to these is the assumption of a centralized overview of the problem and that the problem does not change until a solution is found. System robustness would increase if path management and routing are truly distributed. For an example of this, we need to look no further than the Internet.

Algorithms inspired by the native behavior of ants have been proposed to solve combinatorial optimization problems, see [Dorigo and Caro, 1999] and references therein. These systems are referred to as swarm intelligence systems, and have been applied to many types of problems, ranging from the traveling salesman problem, sequential ordering, graph coloring, routing in telecommunications networks and so on. Swarm intelligence systems are candidates to meet the requirements of complex path and fault management problems in today's networks.

In previous work, an adaptive, robust and distributed routing and management system has been developed [Helvik and Wittner, 2001]. The system is based on swarm intelligence and combines the behavior of foraging ants with an optimization technique from rare event theory called the cross entropy method. The system, from now denoted Cross Entropy Ants System (CEAS), carry out path management in communication networks in an asynchronous and distributed manner. The overall idea is to have a number of ant-like mobile agents searching for paths in a network. When a path is found the ant backtracks and leaves markings called pheromones in each node. The pheromone values are used by other ants in the search for optimal paths.

In all swarm systems there is a tradeoff between performance and management overhead (number of ant packets). This project focuses on reducing the overhead in terms of ant packets generated in CEAS. The new CEAS, from now on denoted *subpath CEAS*, applies pheromone sharing between ants from different sources going to identical destinations. The numbers of ants as well as the pheromone tables are reduced by letting different sources cooperate in their path search. Pheromone sharing is achieved by making the pheromones destination specific by splitting the main path into several subpaths that are maintained individually.

A description of the original CEAS is given in Chapter 2, followed by a presentation of the new *subpath CEAS* in Chapter 3. The results from a comparative study of the two systems are given in Chapter 5.

1.2 RELATED WORKS

In this section related works regarding the topics in this project are presented. Note that the selected publications do not represent an exhaustive list, and some works, which are considered significant by others, may not be included here.

[Dorigo and Caro, 1999] gives an overview of basic biological findings on real ants and their artificial counterparts in the swarm algorithms. It describes combinatorial optimization and routing in communications networks where ant al-

gorithms may be applied.

The Cross Entropy Ants System [Helvik and Wittner, 2001], is an adaptive, robust and distributed routing and management system, which forms the foundation of the work presented in this report. The algorithm is based on Rubinstein's method for stochastic optimization [Rubinstein, 1999]. Previous works have shown that CEAS are robust and efficient in solving complex optimization problems. Dependable routing in terms of finding primary paths with backup paths or simple cyclic paths (p-cycles) is investigated in [Wittner and Helvik, 2002, Wittner et al., 2005]. CEAS used in network management are examined in [Heegaard et al., 2005] and a demonstrator that visualizes the ant based routing and monitoring on small routers was implemented in [Heegaard and Fuglem, 2006].

The overhead of CEAS is measured in the number of ant packets, size of routing tables, path evaluations and pheromone updates. Several approaches to reduce the overhead in CEAS have been studied. [Wittner et al., 2003b,a] uses CEAS to find resources in networks introducing cooperation between ants with partly overlapping QoS profiles, however the approach is different from the cooperation strategy suggested in this report. Another approach to reduce management overhead in CEAS is introduced in [Heegaard and Wittner, 2006]. The overhead is reduced by self-tuned packet rate control. Self-tuned rate control can be used to increase the ant rate when failures occur, or when a path search converge. A self-tuned rate control is likely to be effective in different CEAS applications. A third approach to limit managements overhead is described in [Heegaard et al., 2004]. It uses the concept of *elite selection* in which only ants following paths with cost values among the best so far are triggering a pheromone update. The *elite selection* are further examined and included in the new CEAS system presented in this report.

1.3 RESEARCH METHODS

The research performed in this work uses common research methods in order to ensure sound and reproducible results. As illustrated in Figure 1.1 it starts with a research hypothesis that is evaluated by simulations. The following steps outline the general research process:

Hypothesis

The work is based on a research hypothesis. The hypothesis typically poses a question such as "Will the new algorithm perform better than the original one?" The main goal with the rest of the process is to try to answer the question.

The main hypotheses in this project are given below:

1. Will the new CEAS perform better than the original one?
2. Is elite selection equally efficient in the new system as in the original one?
3. Will cyclic paths have influence on the new CEAS?
4. Is it possible to achieve an efficient cooperation between different sources?
5. Is it possible to reduce the amount of management packets with the new algorithm?

For more about the hypothesis tested in this work see Section 3.4, where the expected performance of the new system is addressed.

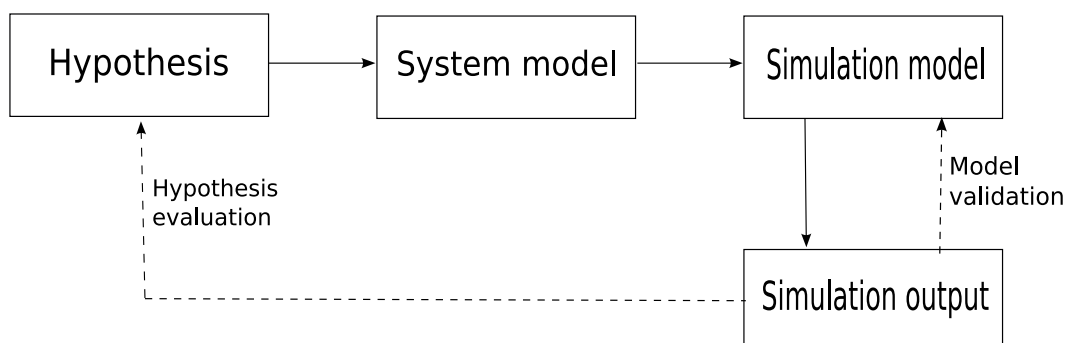


Figure 1.1: Research process

Investigation method

Simulations may incorporate a lot of details of a system, although an analytical model would possibly give better understanding of underlying factors. With an analytical model a wide range of parameters can be examined using significantly less time compared to simulations, however most of the issues considered in this work are too complex to be fully captured in an analytical model. Therefore, in order to evaluate the hypothesis given in this report, simulations have been employed.

Simulations

For all the simulations, Network Simulator 2 (NS2)¹ has been utilized. NS2 is a discrete event simulator with software packets to simulate a communication network from the link layer and up, for both wired and wireless networks. NS2 routing modules, that was first developed in [Helvik and Wittner, 2001], have been used as a foundation for the new simulator. The modules are written in C++ and have been modified and expanded to implement the new subpath system. 20 independent replications have been run for each simulation, and the resulting 95 percent confidence intervals have been calculated. The simulation model is described in detail in Chapter 4.

Results

The results obtained from the simulations are used for both model validation and evaluation of the hypothesis. The results are first compared to the expected logical behavior of the simulation model. If the simulation shows unexpected behavior the initial studies are reevaluated to find a logical explanation. If no logical explanation is found, further testing of the simulator code is carried out to discover possible flaws. Eventually the results are used to evaluate the hypothesis. An evaluation of the hypothesis can best be done after a variation of input parameters and exploration of the parameter space.

¹For more information about NS2 see <http://www.isi.edu/nsnam/ns/>

CHAPTER 2

CROSS ENTROPY ANTS SYSTEM

The Cross Entropy Ants System (CEAS), first introduced in [Helvik and Witter, 2001], forms the foundation for the work presented in this report. The CEAS uses a cross entropy based method to guide mobile agents finding paths in a network. It is a distributed algorithm based on Rubinstein's method for stochastic optimization [Rubinstein, 1999]. The overall idea is to have a number of ant-like mobile agents searching for paths in a network. When a path is found the ant backtracks and leaves markings, called pheromones, in each node. The pheromone values are used by other ants in the search for optimal paths. In this Chapter the functionalities of the original Cross Entropy Ants System are described.

2.1 CROSS ENTROPY

A *cross-entropy method* [de Boer et al., 2002] involves an iterative procedure where each iteration can be broken down into two phases:

1. Generate a random data sample according to a specified mechanism.
2. Applying Cross Entropy and the sampled data, update the parameters of the random mechanism such that the probability of producing a "better" sample in the next iteration is increased.

Cross-entropy is a very useful tool for solving many difficult and often NP-hard problems. It defines a precise mathematical way of deriving fast learning rules, these can for example be used in rare event simulations in reliability and performance analysis of telecommunication systems. [de Boer et al., 2002]

2.2 THE CEAS ALGORITHM

Real ant colonies have a foraging behavior finding shortest paths between a food source and the nest. Ants deposit on the ground a substance called pheromones. Ants can smell the pheromones and tend to probabilistically follow paths with strong pheromones. Ants tend to travel approximately with the same speed while depositing pheromones at approximately the same rate. The ants that follow short paths will pass obstacles faster, hence seen from the other side of the obstacle there will be more ants from the shortest path. When ants then approach the obstacle from that other side they smell stronger pheromones on the shortest path, hence when ants are traveling back and forth the shortest path will be chosen more frequently from both sides. For details see [Dorigo and Caro, 1999] and references therein.

The artificial ants applied in CEAS are, unlike their biological counterparts, not leaving any pheromones when they move forth. When they arrive at the target the path they followed are evaluated and weighted relative to historical paths. Then they are returned the same way back leaving pheromones relative to the performance of their path. The CEAS algorithm basically consists of three functionalities, *forward search*, *path evaluation* and *pheromone updates*. The functionalities are described in detail in the following.

2.2.1 Forward search

A sequence of mobile agents, from now on called forward ants, is sent out from a source to a destination. There are two different types of forward ants, *exploration ants* and *maintenance ants*. A maintenance ant, also called normal ant, chooses the next hop probabilities, $p_{t,ij}$, based on the pheromone values in the node according to Equation 2.1, where $T_{t,ij}$ is the pheromone value at time t over interface j in node i for ant species of a specific source destination pair. Exploration ants use no information in the nodes but choose the next hop randomly.

$$p_{t,ij} = \frac{T_{t,ij}}{\sum_{\forall k} T_{t,ik}} \quad (2.1)$$

2.2.2 Path Evaluation

When an ant reaches its destination, a cost value, $L(\pi)$, for the path is calculated. Based on this cost value, the Boltzmann function is applied as a performance function, Equation 2.2. Historical performance values are weighted decreasingly as time goes by, giving a geometrical weighted average performance. Equation 2.3 shows the autoregressive version of the averaging function. In the applied Boltzmann function, $L(\pi)$ is the potential function and γ is the control parameter, from now on called temperature. Figure 2.1 shows the Boltzmann function and we see that a decreasing temperature, γ , puts an increasing weight on the smaller path costs relative to larger cost values. The temperature can be found from Equation 2.4. It is calculated through a first order Taylor expansion to avoid storing all previous cost values (see [Helvik and Wittner, 2001] for details). The temperature will decrease and stabilize when more ants arrive and the empirical routing tables (pheromone tables) converge.

$$H(\gamma, \pi) = e^{-\frac{L(\pi)}{\gamma}} \quad (2.2)$$

$$h_t = \beta h_{t-dt} + (1 - \beta) e^{-\frac{L(\pi_t)}{\gamma_t}} \quad (2.3)$$

$$\gamma_t = \frac{B + L(\pi_t) \cdot \exp\left(-\frac{L(\pi_t)}{\gamma_t + \Delta t}\right)}{\left(1 + \frac{L(\pi_t)}{\gamma_t + \Delta t}\right) \cdot \exp\left(-\frac{L(\pi_t)}{\gamma_t + \Delta t}\right) + A - \rho \frac{1 - \beta^{M+1}}{1 - \beta}}$$

where :

$$\begin{aligned} A &\leftarrow \beta \left(A + \left(1 + \frac{L(\pi_t)}{\gamma_t} \right) \exp\left(-\frac{L(\pi_t)}{\gamma_t}\right) \right) \\ B &\leftarrow \beta \left(B + \left(1 + L(\pi_t) \exp\left(-\frac{L(\pi_t)}{\gamma_t}\right) \right) \right) \\ \gamma_t - \Delta t &\leftarrow \gamma_t \\ M &\leftarrow M + 1 \end{aligned} \tag{2.4}$$

The initial values are $A = B = M = 0$ and $\gamma_0 = -\frac{L(\pi_0)}{\ln(\rho)}$

$\beta \in [0, 1]$ is the autoregressive memory factor, typically close to one.

$\rho \in [10^{-6}, 10^{-2}]$ is a search focus parameter.

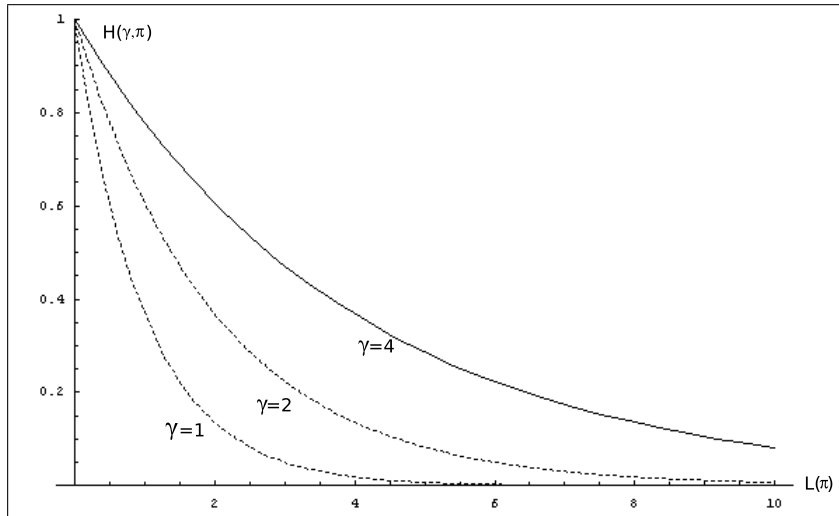


Figure 2.1: Illustration of the Boltzmann function (Equation 2.2) Decreasing temperature, γ , puts an increasing weight on the smaller path costs.

2.2.3 Backward updates

A backward ant is returned to update pheromone values in each intermediate node based on the path evaluation. The pheromone value can be calculated by equation 2.5, where M is the number of previously arrived backward ants and T_j is the pheromone value of outgoing link j . γ_0 is the temperature of the last arriving ant, γ_{-1} is the temperature of the ant that arrived just before that and so on. The equation is unsuited for solving in a network node since it is transcendental¹ and the storage of a potentially infinite number of path costs is required. Equation 2.6 that is a first order Taylor expansion of each term in Equation 2.5 is therefore used as well as auto regression, see [Helvik and Wittner, 2001] for further details.

$$T_j = \sum_{i=-M}^0 I(\{j\} \in \pi_0) \beta^{-i} \exp\left(\frac{L(\pi_i)}{\gamma_0}\right) \quad (2.5)$$

$$T_j = I(\{j\} \in \pi_0) e^{-\frac{L(\pi_0)}{\gamma_0}} + A_j + \begin{cases} -\frac{B_j}{\gamma_0} + \frac{C_j}{\gamma_0^2}, & \frac{1}{\gamma_0} \left(\frac{B_j}{2C_j}\right) \\ -\frac{B_j^2}{4C_j}, & \text{otherwise} \end{cases}$$

where :

$$\begin{aligned} A_j &\leftarrow \beta(A_j + I(\{j\} \in \pi_0) e^{-\frac{L(\pi_0)}{\gamma_0}} (1 + \frac{L(\pi_0)}{\gamma_0} (1 + \frac{L(\pi_0)}{2\gamma_0}))) \\ B_j &\leftarrow \beta(B_j + I(\{j\} \in \pi_0) e^{-\frac{L(\pi_0)}{\gamma_0}} (L(\pi_0) + \frac{L(\pi_0)^2}{\gamma_0})) \\ C_j &\leftarrow \beta(C_j + I(\{j\} \in \pi_0) e^{-\frac{L(\pi_0)}{\gamma_0}} \cdot \frac{L(\pi_0)^2}{2}) \end{aligned} \quad (2.6)$$

¹A transcendental number is a (possibly complex) number that is not the root of any integer polynomial, meaning that it is not an algebraic number of any degree. [Weisstein, Eric W. "Transcendental Number." From MathWorld—A Wolfram Web Resource. <http://mathworld.wolfram.com/TranscendentalNumber.html>]

CHAPTER 3

PHEROMONE SHARING

The performance of CEAS, described in Chapter 2 depends much on the ant rate. A high ant rate combined with a high beta value (long memory) enables CEAS to solve even NP complete problems efficiently [Helvik and Wittner, 2001]. This means that there is a tradeoff between performance and overhead in terms of ant packets. To reduce overhead and increase scalability additional features have been proposed. The *elite selection* functionality proposed in [Heegaard et al., 2004] ensures that only paths with relatively low cost, compared to historical costs, are sent back to update the pheromone tables. The *elite selection* has shown improved performances both in the speed of convergence and the quality of the path found.

The focus of the work presented in this report is to reduce the size of pheromone tables (routing tables) and, like in [Heegaard et al., 2004], to reduce overhead in terms of ant packets. The strategy suggests cooperation between ants from different sources going to identical destinations. The general idea is to make the pheromone values to be destination specific instead of maintaining distinct pheromone values for each source-destination pair. This is achieved by splitting the mainpath into subpaths that are maintained individually. The new Cross Entropy Ants System, denoted *subpath CEAS*, is described in the following.

3.1 SUBPATH CEAS

The objective of pheromone sharing is to reduce the size of routing tables and by this make CEAS more scalable. Hopefully another benefit from these methods is faster convergence of pheromone tables, and less overhead in terms of ant packets as well. In current implementations of CEAS , the routing tables

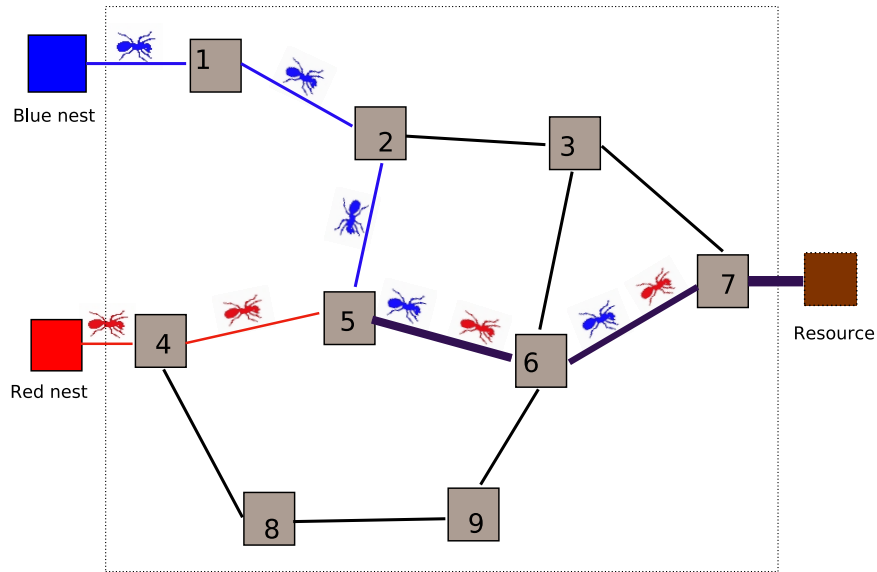


Figure 3.1: In the figure three subpaths and pertaining pheromones are shared between red and blue ant species. The subpaths are $\{5,6,7,R\}$, $\{6,7,R\}$ and $\{7,R\}$

consist of separate pheromone values for each active source-destination pair. Frequently a node is the requested resource of several users and becomes the destination of many different sources, the situation is illustrated in Figure 3.1. According to *Bellman's principle of optimality*¹ this causes ants from different source nodes to follow identical paths when they approach the destination. If the different sources cooperate when searching for the best path to a given destination, the search will converge faster and lead to less overhead in the network due to number of ants necessary. A pheromone value in intermediate nodes will no longer be specific for one ant-specie i.e. a pair of source and destination, but indicate the best path from the current node to a specific destination.

In the following the required extensions and changes to the basic functionalities in CEAS to enable cooperation between ants are described. A subpath strategy is introduced that considers cost from each intermediate node toward the destination. For example if the mainpath is $\{1\ 2\ 3\ 4\}$, it will consist of the following three subpaths; $\{3\ 4\}$, $\{2\ 3\ 4\}$ and $\{1\ 2\ 3\ 4\}$. In the following a path, π_{sd} , between the source and destination will be denoted a mainpath and a path π_{id}

¹Bellman's principle of optimality says that if we have found an optimal path from A to B through C, we have also found an optimal path from A to C and from C to B

from one of the nodes to the destination will be denoted a subpath.

3.1.1 Forward search and path evaluation

The cost from each node along the mainpath must be collected during forward search. This will increase the size of ant packets to some extent. At the destination a temperature, γ_{id} , needs to be calculated for each of the subpaths, π_{id} , by Equation 3.1 which is a subpath indexed version of Equation 2.4. This will result in increased computational overhead per ant in the destination node.

$$\gamma_{id,t} = \frac{B + L(\pi_{id,t}) \cdot \exp\left(-\frac{L(\pi_{id,t})}{\gamma_{id,t+\Delta t}}\right)}{\left(1 + \frac{L(\pi_{id,t})}{\gamma_{id,t+\Delta t}}\right) \cdot \exp\left(-\frac{L(\pi_{id,t})}{\gamma_{id,t+\Delta t}}\right) + A - \rho \frac{1-\beta^{M+1}}{1-\beta}}$$

where :

$$\begin{aligned} A &\leftarrow \beta \left(A + \left(1 + \frac{L(\pi_{id,t})}{\gamma_{id,t}} \right) \exp\left(-\frac{L(\pi_{id,t})}{\gamma_{id,t}}\right) \right) \\ B &\leftarrow \beta \left(B + \left(1 + L(\pi_{id,t}) \exp\left(-\frac{L(\pi_{id,t})}{\gamma_{id,t}}\right) \right) \right) \\ \gamma_{id,t} - \Delta t &\leftarrow \gamma_{id,t} \\ M &\leftarrow M + 1 \end{aligned} \tag{3.1}$$

3.1.2 Backward updates

In the original Cross Entropy Ants System, described in Chapter 2, all pheromones were updated from the temperature of the mainpath. By introducing subpaths and pheromone sharing, each subpath will have its own temperature and the pheromones in a node are updated by Equation 2.6 on the basis of the corresponding subpath and its temperature. The backward ants need to carry temperatures and cost values for each subpath. This will increase the size of backward ants to some extent, although no extra computations during backward updates are introduced.

3.2 ELITE SELECTION

In the original CEAS, paths from all incoming forward ants are returned to update pheromone values. This results in the temperature being calculated and a backward ant returned even if the path cost is very poor. In [Heegaard et al., 2004] the concept of *elite selection* is introduced in order to reduce the overhead of backward ants carrying insignificant updates. Only path costs within a certain bound relative to the best path costs found will trigger pheromone updates. The elite selection criterion is given by Equation 3.2. (for details see [Heegaard et al., 2004]). CEAS with elite selection has shown improved performances both in the speed of convergence and the quality of the path found. When elite selection is implemented with subpath CEAS, elite selection must be performed on each subpath. If one of the subpaths satisfies its elite criterion, a backward ant is returned, however pheromone updates will only be performed in nodes approved by elite selection. Since all subpaths need to be disapproved by elite selection to reduce overhead in terms of backward ants, this reduces the benefits of elite selection. However, elite selection's focus on good paths will still potentially increase the speed of convergence.

$$L(\pi) \propto -\gamma \cdot \ln(\rho) \quad (3.2)$$

Explorer ants

As mentioned in Chapter 2 there are two different types of ants, *normal ants* and *explorer ants*. [Heegaard et al., 2004] does not address explorer ants although there is a question if *elite selection* should be performed on all ant types or only on normal ants. Three different elite selection strategies are examined in this work, namely, 1) *No elite selection*, 2) *Elite selection on all ant types* and 3) *Elite selection only on normal ants*, e.i. explorer ants are not included in calculations of the elite criterion and they are always returned as backward ants. Note that with elite selection two temperatures are maintained, one to

calculate the elite criterion and another to calculate pheromone updates. The elite selection strategies differ in how those two temperatures are updated. If elite selection is performed on all ant types, the first temperature, controlling the elite criterion, is updated by all incoming ants, while the second temperature, controlling pheromone updates, is only updated by ants approved by elite selection. However if elite selection is only performed on normal ants, the temperature controlling the elite criterion is only updated by normal ants, while the temperature controlling pheromone updates is updated by all explorer ants and the normal ants approved by the elite criterion. The effects of different elite selection strategies are investigated in Chapter 5.2 for both the subpath CEAS and the original CEAS.

3.3 CYCLIC PATHS

In the original CEAS cycles in a path are not considered a problem. Cyclic paths will probably under perform and soon be discarded by elite selection if elite selection is implemented. One of the drawbacks of the subpath approach is the increased number of temperature calculations in the destination node, one for each hop. Cyclic paths can be very long and result in an excessive amount of unnecessary computations in the destination node. Another issue with cycles and the *subpath CEAS*, is that cycles will create several different subpaths from each intermediate node and by this trigger several pheromone updates in each node caused by one single backward ant. This will probably disturb the algorithm and make it less effective. Some modifications to the algorithm should therefore be included to handle cyclic paths in the subpath CEAS. There are several options on how to treat cycles in a path, they differ in how much information from the traversed path they preserve and how much computational overhead they add. One should note that increased computational overhead introduced by cycle treatment will result in fewer calculations in terms of path evaluations and pheromone updates, and decreased network load because of shorter backward paths.

Three different approaches on how to treat cycles are proposed in Table 3.1. *No cycle treatment* may result in long mainpaths and a lot of subpaths, and for

Cycle treatment method	Cons	Pros
No cycle treatment	Possible long paths resulting in increased temperature calculations and pheromone updates. Increased network load because of long backward paths. Several pheromone updates in each node reducing focus on the best path.	No need for functionalities to detect or remove cycles.
Prevent cycles during forward search	Loss of information. Increased first through time.	Easy to detect cycles, no extra computations in destination node. Limited path length reduces network load.
Remove cycles in destination node	Increased computations in destination. Some loss of information in destination.	Less temperature calculations and shorter backward paths than no cycle treatment.

Table 3.1: Comparison of the three cycle treatment methods

each subpath a temperature needs to be calculated. During backward updates this will lead to several pheromone updates in each node, possibly disturbing the algorithm. *Preventing cycles during forward search*, means to simply drop all ants going in cycles, this may result in a long first through time. Removing all cycles in a path before doing path evaluations is relatively easy, although when this is done in a straight forward manner, the remaining path may not be the best path indicated by the cyclic path, hence some information is lost. A way to maintain all information from a cyclic path is to find all possible non-cyclic subpaths within the mainpath. This is a costly operation and not suited to be applied for each ant. To implement a sophisticated cycle removing algorithm will most likely not improve the performance very much relative to the increased computational burden. The three cycle treatment methods suggested here will be examined in Chapter 5.2 for the new subpath CEAS and the original CEAS as well.

3.4 PERFORMANCE

With the subpath algorithm, the following aspects are expected to increase performances:

- The pheromone updates in intermediate nodes are updated on what costs the node sees toward the destination, not what the source node sees.
- The pheromone updates will not be affected by poor path choices preceding the node.

- The above aspects will probably result in faster convergence of pheromones near the destination, which will shrink the search space for subsequent ants.
- Possibility of cooperation between ants from different sources going to identical destination. A successful cooperation will increase performances.
- A new connection may benefit from pheromones placed by mature connections.

A fast convergence in nodes closer to the destination may have both positive and negative effects on the convergence in preceding nodes dependent of network topology. For example in a topology such as Figure 5.1, where an ant in the source has two options, going to node four or node five. In this topology a fast convergence in node six will not necessary have any impact on the forwarding in the source node, because both interfaces are equally influenced. However, if the interfaces resulted in two disjoint paths toward the destination, an early convergence in nodes close to the destination on one of the interfaces could result in better cost values on this interface even though the best path between source and destination is on the other interface.

Overhead

The memory consumption in the intermediate nodes are decreased with the subpath CEAS. In a network with N nodes the maximum number of source-destination pairs is $N \cdot (N - 1) = O(N^2)$, using the original source-destination specific pheromones. In the subpath CEAS a routing entry is destination specific, and the maximum routing table will be reduced to $N - 1$, that is $O(N)$. In a network with 100 nodes the worst case routing table size will be reduced from 9900 to 99.

Although an increased performance is expected with subpath CEAS compared to the original CEAS it does not come for free. Subpath CEAS puts an increased computational load on the destination node for each arriving ant. The Path from each node visited by an ant needs to be evaluated individually. The worst case number of temperature calculations is limited by the TTL field. In the

original CEAS only one temperature calculation is necessary per ant, two with elite selection. It is possible to let each intermediate node maintain their own temperature and do their own path evaluations, but it is a not straight forward how such a strategy can be integrated with elite selection.

With an efficient cooperation between sources in their path search the ant rate per source can be reduced. If a faster convergence is obtained, the ant rate can be reduced and still perform adequately. With a method to detect convergence the ant rate could be reduced at the time of convergence. When comparing overhead of different systems in Chapter 5 the overhead is measured at the time of convergence, hence a fast convergence will reduce the overhead of the system. One should note that the ant rate during the search is not reduced by this, i.e. the destination must still be able to cope with the maximum ant rate.

CHAPTER 4

SIMULATION MODEL AND IMPLEMENTATION

The algorithm in the Cross Entropy Ants System (CEAS) involves a large number of stochastic processes working in parallel, hence the system is difficult to examine analytically. CEAS is therefore studied in a series of simulation experiments in Network Simulator 2 (NS2)¹. NS2 is a discrete event simulator including software packets to simulate a communication network from the link layer and up, for both wired and wireless networks.

4.1 SIMULATOR BASICS

NS2 is a well tested simulator package that is implemented as a mix of C++ classes in a kernel performing heavy computations and OTcl² classes which act as the interface to users. Simple usage of NS2 does not require any source code knowledge, however in complex simulations, modifications to the NS2 protocols or even totally new protocols need to be implemented. The NS2 packet includes different transport protocols, routing protocols, scheduling disciplines and traffic generators.

There are basically three entity types constituting a NS2 simulator, those are *nodes*, *links* and *agents*. When designing a new simulator, nodes are created and connected by links. *Agents* are specified and bound to the nodes, they act as the sources and sinks for data and management packets. Traffic generators are also added and a simulation scenario specified. A simulation example is shown in Figure 4.1.

¹For more information about NS2, see <http://www.isi.edu/nsnam/ns/>

²OTcl, short for MIT Object Tcl, is an extension to Tcl/Tk for object-oriented programming. (<http://otcl-tclcl.sourceforge.net/otcl/>)

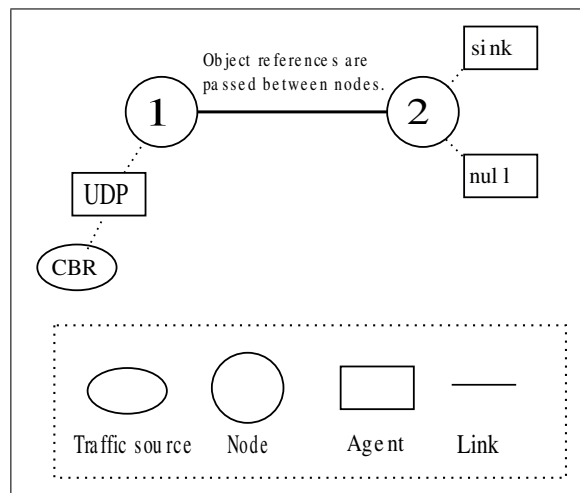


Figure 4.1: NS2 simulation example

It is essential for researchers, which are evaluating new protocols and schemes, to be able to implement new functionalities not covered in NS2. In [Helvik and Wittner, 2001] a new routing module was implemented that supports CEAS functionalities. Standard routing implementations in NS2 are implemented as *routing modules*. In general, every *routing module* consists of three function blocks:

- *Routing agent* - Exchanges routing packets with neighbor nodes.
- *Route logic* - Uses the information gathered by routing agents to perform the route calculations.
- *Classifiers* - Use the computed routing table to perform packet forwarding.

When implementing a new routing protocol it is not necessary to implement all of these three blocks. In the CEAS routing module, illustrated in Figure 4.2, all alterations of routing data are performed by the *routing agent*, and there is no separate *route logic* block. *Classifiers* provide a way to match a packet against some logical criteria and retrieve a reference to another simulation object based on the results. The *swarm classifiers* identify swarm packets and map them to the *swarm module* where they are put into a *swarm packet queue*. Forwarding based on pheromone tables are performed by the *swarm ragent*. The swarm packets are fetched from the queue by *swarm ragents* (routing agents) and the CEAS data are read. *Ragents* are reinitialized when a new swarm packet is

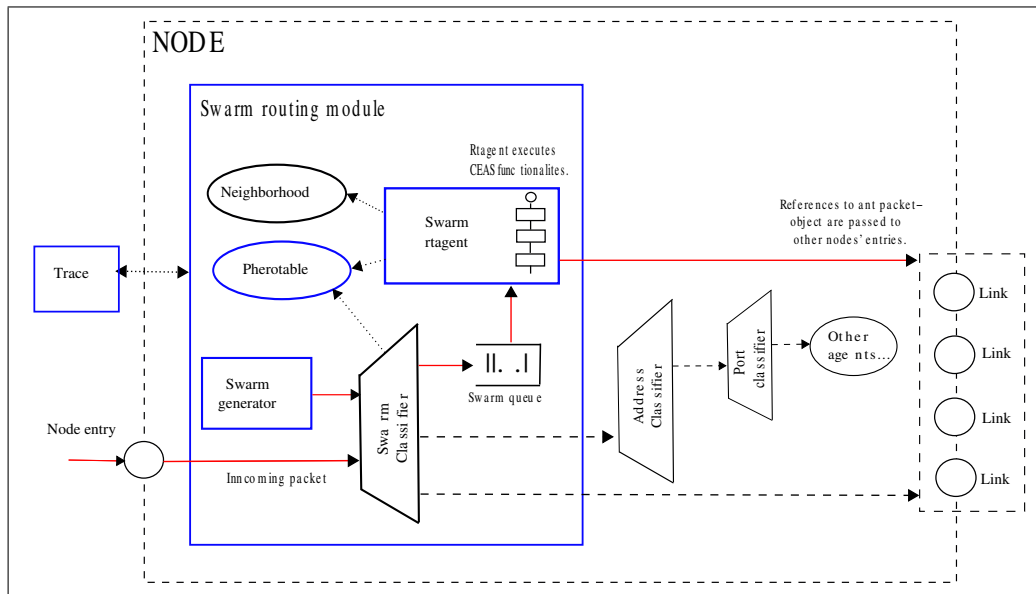


Figure 4.2: Structure of a CEAS node

ready to be processed. *Rtagents* are implemented as state machines that execute CEAS functionalities like *forward search*, *path evaluation* and *pheromone updates*. The *swarm rtagents* maintain temperature auto regression parameters if the current node is a destination node. During forward search *rtagents* look up pheromone values in the pheromone tables, and during backward updates they alter those pheromone tables.

To summarize, the states of the system are saved both in nodes, in terms of pheromone tables and temperatures, and in data packets, in terms of ant behavior type (forward/backward). Only the packet references are passed between nodes. The nodes contain their own logic, and they may have different functionalities such as generator, router or destination. The red arrows in Figure 4.2 indicate how ant packets are handled in a CEAS node. Classes modified to implement the subpath system are colored blue in the figure.

In this work the *CEAS rtagent* has been rewritten in order to implement the new subpath CEAS presented in Chapter 3. Each node has its own *rtagent* and it includes all the functionalities in the CEAS algorithm performed on a per packet basis. The pheromones have been changed to allow destination specific pheromones. The temperature auto regression parameters have been changed to be subpath specific, and pheromone IDs, unique for each connection, are in

the new implementation merely used in statistics. Since all the logic is located in the *rtaagent* the payload in swarm packets only contains swarm data. This includes *ant type*, *path cost*, *temperature* and *route record*. The swarm packets have been expanded such that link costs and temperatures are implemented as lists indexed by the route record. Functionality for different elite selection strategies and cycle treatment methods have been implemented in the new *rtaagent*, and new parameters for elite selection and cycle treatment are added to the TCL interface in the *generator* class. This allows parameter passing between TCL user scripts and NS2 C++ classes. Some modifications and new functions in the *trace* class were also implemented to meet requirements of the case studies presented in this work. For access to the source code of the new NS2 modules see Appendix A

4.2 PRODUCTION

All simulations in this report are run with 20 replications with different seeds for the random generator. To decrease the processing time, simulations have been carried out on a server cluster at the Department of Telematics at the Norwegian University of Science and Technology (NTNU). The simulation output from all the replications are synchronized and post processed with the AWK³ programming language. Explorer ants are tagged during sampling and excluded in all calculations except in the forward ant and backward ant counters. The plots from the simulation results have been generated with gnuplot⁴. Figure 4.3 illustrates the simulation process.

³AWK is a general purpose programming language designed for processing text-based data

⁴Gnuplot is a versatile command-line driven program that can generate plots of functions and data.

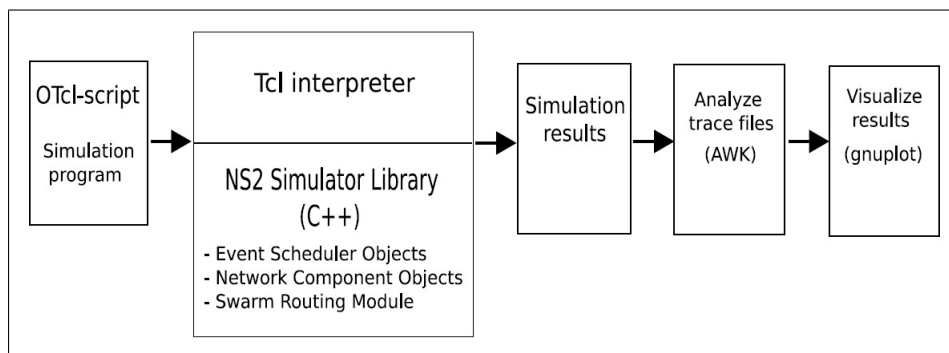


Figure 4.3: Simulation process.

4.3 PARAMETERS

The input parameters to the simulator are given in the TCL user script. Default values are listed below.

Seed: 171175 + simid (A different simid is given for each replication)

Simulation time: 30 000 seconds (simulated)

Ant-rate normal: 1.0 per second

Ant-rate explorer: 0.1 per second

(Ratio between explorer ants and normal ants is 1:10)

Init phase: 10 / ant-rate

(All ants are explorers in the init phase)

TTL: 130 hops (Time To Live)

Processing delay: 0

(The total delay is specified for each link in the topology)

Beta: 0.998

(Evaporation, for details see [Helvik and Wittner, 2001])

Rho: 0.01

(Search focus, for details see [Helvik and Wittner, 2001])

Elite selection: Elite selection only on normal ants

(For details see Chapter 3.2)

Cycle treatment: Remove cycles in destination

(For details see Chapter 3.3)

4.4 TOPOLOGIES

Two different topologies are used in the case studies, a ten node network and a 216 node nationwide communication network. The Ten node network, depicted in Figure 5.1 was chosen because it has a regular structure that should be well suited for cooperation and easy to examine. The 216 node network, depicted in Figure 5.12 is the former backbone topology of a major Internet provider in Norway. It consists of 10 core routers in a partly meshed topology, a ring based edge network with a total of 46 routers, and a dual homing access

network with 160 access routers. The relative transmission capacities are 1, 1/4 and 1/16 for core, edge and access links respectively. The average number of hops between the access routers is 6.37. This topology was chosen to provide a realistic setting for the new subpath CEAS with cooperation.

Dynamic environments

NS2 has functionalities to simulate network dynamics such as link failures. In this work the systems are studied in three phases, first, the initial phase where sources start their path search, second, the failure phase where one or more network links fail, and third, the restoration phase where links are restored. The cost values are defined as the link delay. The delays of each link are specified in the topology and are constant. Since CEAS ants are not influenced by traffic load in the case studies carried out here, no transient time is necessary. However, the performance in the failure phase and restoration phase are dependent on how the system performed during previous phases. The different systems are therefore easiest compared in the initial phase when the conditions are known and equal for all systems, i.e. no existent pheromones in the network.

CHAPTER 5

CASE STUDIES

This chapter presents simulation studies of the subpath Cross Entropy Ants System (CEAS). The different case studies are divided into the following three sections:

Section 5.2, Elite selection and cycle treatment:

Different elite selection strategies and cycle treatment methods are examined. Both the original CEAS and the new subpath CEAS, described in Chapter 3, are studied with different elite selection strategies and cycle treatment strategies.

Section 5.3, Subpath CEAS versus original CEAS:

The performance of the subpath CEAS is compared to the original CEAS in detail. Reduced ant rate is examined to disclose a possible overhead reduction in the subpath CEAS.

Section 5.4, Pheromone sharing:

Cooperation between sources through pheromone sharing is studied. The cooperative systems are based on the subpath CEAS and are compared to the original CEAS and the subpath CEAS without cooperation as well.

5.1 PERFORMANCE METRICS

The following performance metrics are applied when comparing the systems in the different case studies:

Average cost - Average cost between source and destination. The average costs are plotted with 95 percent confidence intervals.

Most popular path - Most popular path the last 100 seconds for the majority of the simulation replications.

Path convergence - The share of normal ants following the most popular path. The path convergence is plotted with 95 percent confidence intervals.

No of forward ants - Number of forward ants generated.

No of backward ants - Number of backward ants returned.

No of tours - Total number of forward ants and backward ants.

No of temperature calculations - Total number of temperature calculations in the destination node.

Time to best theoretical path found - Point in time when the best theoretical path is first followed by a normal ant. The best path is not considered detected when only explorer ants have followed the path, because an explorer ant following the best path is only a coincidence. When the simulation starts, all ants are explorers for a small amount of time, hence the shortest time to best theoretical path found is when the first normal ant is generated.

Time to best path found - Point in time when the best path within a given time interval was first discovered by a normal ant. When the simulation starts, all ants are explorers for a small amount of time, hence the shortest time to best path found is when the first normal ant is generated.

Best path found - Best path found by a normal ant within a given time interval.

Convergence time - Point in time when 80 percent of the normal ants follow identical paths with respect to path cost. The percentage is calculated for each 100 second, hence the shortest convergence time is 100 seconds.

Converged value - Cost of converged path. The converged path may not be the theoretical best path, however the theoretical best path may be found at a later point of time. The best converged value among all replications shows if the theoretical best path was ever found. The worst converged value shows the worst miss among the replications, i.e. the highest path cost one of the replications converged to.

5.2 ELITE SELECTION AND CYCLE TREATMENT

Elite selection [Heegaard et al., 2004] showed improved performance applied to the original CEAS because elite selection increases the focus on the best paths and reduces overhead by not returning unnecessary backward ants. Increased performance of elite selection is expected for the subpath CEAS as well, however backward ants will be returned as long as one of the subpaths is approved by elite selection, hence more ants are returned as backward ants. The studies in this section are carried out in order to see how different elite selection strategies and cycle treatment methods affect the Cross Entropy Ants System. The different strategies are applied to both the original system and the subpath system, in order to see if there are differences between the two systems with respect to various strategies, e.i. are one cycle treatment preferable in both the subpath CEAS and the original CEAS?

Some questions concerning elite selection and explorer ants are not addressed in [Heegaard et al., 2004], namely if exploration ants should be included in the elite selection functionalities. If exploration ants are discarded by elite selection it is possible that backup paths will not be marked during a stable phase. This may cause the system to react slower to network dynamics. It is also possible that elite selection will narrow the search too much leading to increased convergence times or a premature convergence. A possible solution to these problems is to exclude explorer ants from elite selection functionalities,

hence explorer ants will always be returned to update pheromones. Recalling from Section 3.2 and 3.3, three different elite selection strategies and three different cycle treatment methods are suggested in this report.

The elite selection strategies are:

1. *No elite selection*
2. *Elite selection on all ant types*
3. *Elite selection only on normal ants*, e.i. explorer ants are not used to calculate the elite criterion and are always returned as backward ants.

The cycle treatment methods are:

1. No cycle treatment.
2. Prevent cycles during forward search.
3. Remove cycles in destination before performing path evaluations.

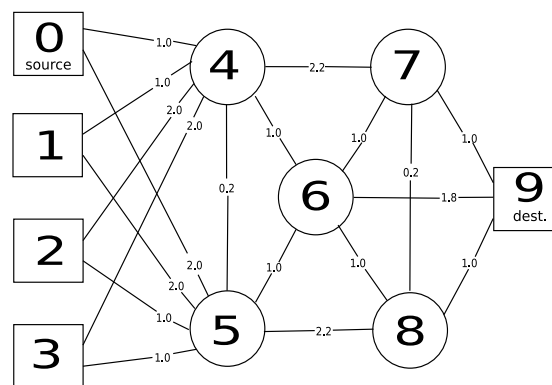


Figure 5.1: Ten node topology, one source

Scenario:

To compare the different elite selection strategies and cycle treatment methods in both the original CEAS and the subpath CEAS, a series of simulation experiments have been carried out applying the ten node topology depicted in Figure 5.1. The single path search from a source node to a destination node is studied. The best path between those two nodes is [0, 4, 6, 9], with a cost of 3.8 ms. Network dynamics are added by implementing a link failure between nodes six and nine after 10 000 seconds and a restoration of the link 7000 seconds later. The failure results in two equally good paths, [0, 4, 6, 7, 9] and [0, 4, 6, 8, 9], both with a cost of 4.0 ms. The systems are compared with

respect to the average cost between source and destination. Nine different simulations are carried out for each system (combinations of three different elite selection strategies and three different cycle treatment strategies). The different strategies are studied in Section 5.2.1 and 5.2.2 for the original CEAS and the subpath CEAS respectively.

Data from the initial phase (0-10000 seconds) from all the simulations are summarized in Table 5.1. The initial phase is the most applicable to compare the different systems since they all have identical initial conditions, i.e. no pheromones in the network. In general the table shows a better first through time and convergence time for the subpath CEAS for all elite selection strategies and cycle treatment methods. The amount of temperature calculation (gamma calculations) are doubled with elite selection and additionally increased around three times with the subpath algorithm. In the following the simulation results, summarized in Table 5.1, are presented in different plots, which forms a better basis for further discussion.

5.2.1 Original CEAS

The three plots in Figure 5.2 show the average cost of normal ants between source and destination for the original CEAS. The three different plots show different cycle treatment methods and the curves show different elite selection strategies. The costs are averaged for each hundred sample, then averaged over 20 simulation replications. The time axis can be separated into three different phases; *initial phase* (0-10000 seconds), *failure phase* (10000-17000 seconds) and *restoration phase* (17000-30000 seconds).

A general observation is that the differences between elite selection strategies are more obvious than the differences between cycle treatment strategies, although with elite selection on all ant types differences between cycle treatments are significant. *Elite selection only on normal ants* shows faster convergence in the initial phase and returns faster to the 3.8ms path when link 6-9 is restored, this applies for all cycle treatments. Increased performance with elite selection was found by earlier work [Heegaard et al., 2004], but the results presented

5.2. ELITE SELECTION AND CYCLE TREATMENT

<i>Elite selection</i>	<i>Cycle treatment</i>	<i>No of tours at time = 10 000</i> (standard error)	<i>No of Gamma calculations at time = 10 000</i> (standard error)	<i>Time to first normal following best path</i> [sek] (standard error)	<i>Time to 80% convergence</i> [sek] (standard error)	<i>Converged value</i> [ms] (min/max)
Original CEAS	Ignore	22 001 (0)	11 006 (4)	89.2 (23.9)	4245 (698)	3.80 (3.8 / 3.8)
	Prevent	21 565 (23)	10 562 (12)	102.5 (35.4)	3050 (757)	3.84 (3.8 / 4.2)
	Remove	22001 (0)	10 999 (3)	79.9 (40.9)	3390 (646)	3.81 (3.8 / 4.0)
	Ignore	21 607 (62)	20 574 (61)	416.4 (147.4)	1220 (346)	3.92 (3.8 / 4.2)
	Prevent	20 378 (102)	19 842 (150)	471.7 (131.6)	750 (241)	3.98 (3.8 / 4.2)
	Remove	20 665 (63)	20 676 (68)	121.7 (43.3)	960 (198)	3.88 (3.8 / 4.2)
	Ignore	21 485 (73)	20 467 (74)	56.6 (13.3)	1150 (249)	3.82 (3.8 / 4.0)
	Prevent	21 013 (109)	20 138 (145)	103.7 (34.4)	795 (247)	3.87 (3.8 / 4.2)
	Remove	21 475 (64)	20 492 (63)	47.6 (16.7)	915 (192)	3.81 (3.8 / 4.0)
Subpath CEAS	Ignore	22 001 (0)	37 778 (118)	25.1 (8.1)	1145 (238)	3.82 (3.8 / 4.2)
	Prevent	21 545 (4)	33 140 (39)	43.1 (13.9)	625 (207)	3.86 (3.8 / 4.2)
	Remove	22 001 (0)	35 630 (48)	25.3 (7.2)	875 (157)	3.80 (3.8 / 3.8)
	Ignore	22 001 (0)	69 009 (189)	151.0 (62.5)	425 (139)	4.02 (3.8 / 4.8)
	Prevent	21 540 (3)	63 342 (143)	140.9 (37.8)	130 (25)	4.25 (3.8 / 5.2)
	Remove	22 001 (0)	65 047 (1425)	87.1 (34.1)	270 (108)	4.00 (3.8 / 5.0)
	Ignore	21 988 (18)	66 547 (38)	14.5 (2.0)	320 (56)	3.80 (3.8 / 3.8)
	Prevent	21 547 (23)	62 641 (201)	38.3 (13.7)	255 (63)	3.81 (3.8 / 4.0)
	Remove	21 985 (3)	64 420 (31)	14.9 (1.4)	205 (15)	3.82 (3.8 / 4.2)

Table 5.1: Simulation output of different elite selection and cycle treatment strategies.

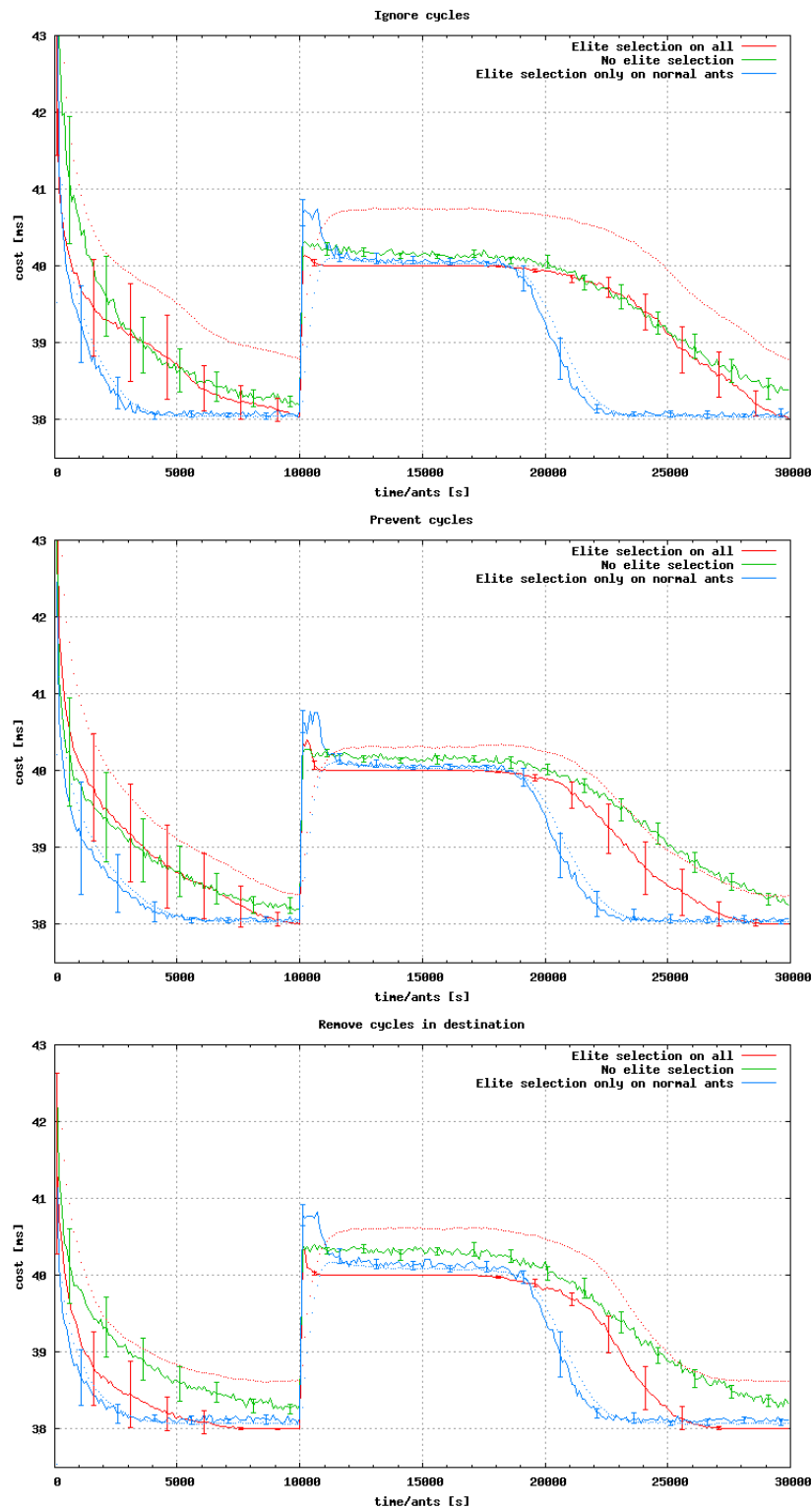


Figure 5.2: Comparison of different elite selection strategies and cycle treatments for the original CEAS. Costs between source and destination plotted with 95 % confidence intervals. Ignore cycles is shown in the top plot, prevent cycles in the middle plot, and remove cycles in the bottom plot.

here also imply that it is a good idea to exclude explorer ants from the elite selection evaluation. The reason is mainly because *elite selection only on normal ants* has the ability to gain from elite selection's focus on good paths although simultaneously keeps a wider search space since explorer ants are never discarded by elite selection.

A small cost peak is observed for *elite selection only on normal ants* right after the link failure. This is because the elite criterion is stricter with this elite selection strategy since the temperature controlling the elite criterion is calculated only from normal ants, thus right after the failure, elite selection will discard incoming normal ants until the elite criterion adapts to the changes. The elite criterion is plotted with dotted lines in Figure 5.2.

The elite criterion respond a little quicker for *elite selection on all ants*, since it is affected directly by explorer ants. It is also observed that the elite criterion calculated from *Elite selection on all ants* are higher than the average normal ant costs since it is calculated from both normal ants and explorer ants, see the red dotted line in the plots. When explorer ants are included in calculating the elite criterion, different cycle treatments will have a larger influence on the elite criterion, thus *elite selection on all* is more affected by cycle treatment strategies, this was observed in Figure 5.2.

5.2.2 Subpath CEAS

Cost plots comparing elite selection strategies similar to the ones for the original CEAS in Figure 5.2 are shown for the subpath CEAS in Figure 5.3. In addition, the *path convergence* with different elite selection strategies for both the original CEAS and the subpath CEAS are compared in Figure 5.4.

A general observation when comparing Figures 5.2 and 5.3 are a faster convergence of the subpath CEAS in all phases. Comparisons of the two systems are further discussed in Section 5.3.

The subpath system shows similar results as the original system with respect to different elite selection strategies, although the differences between strategies

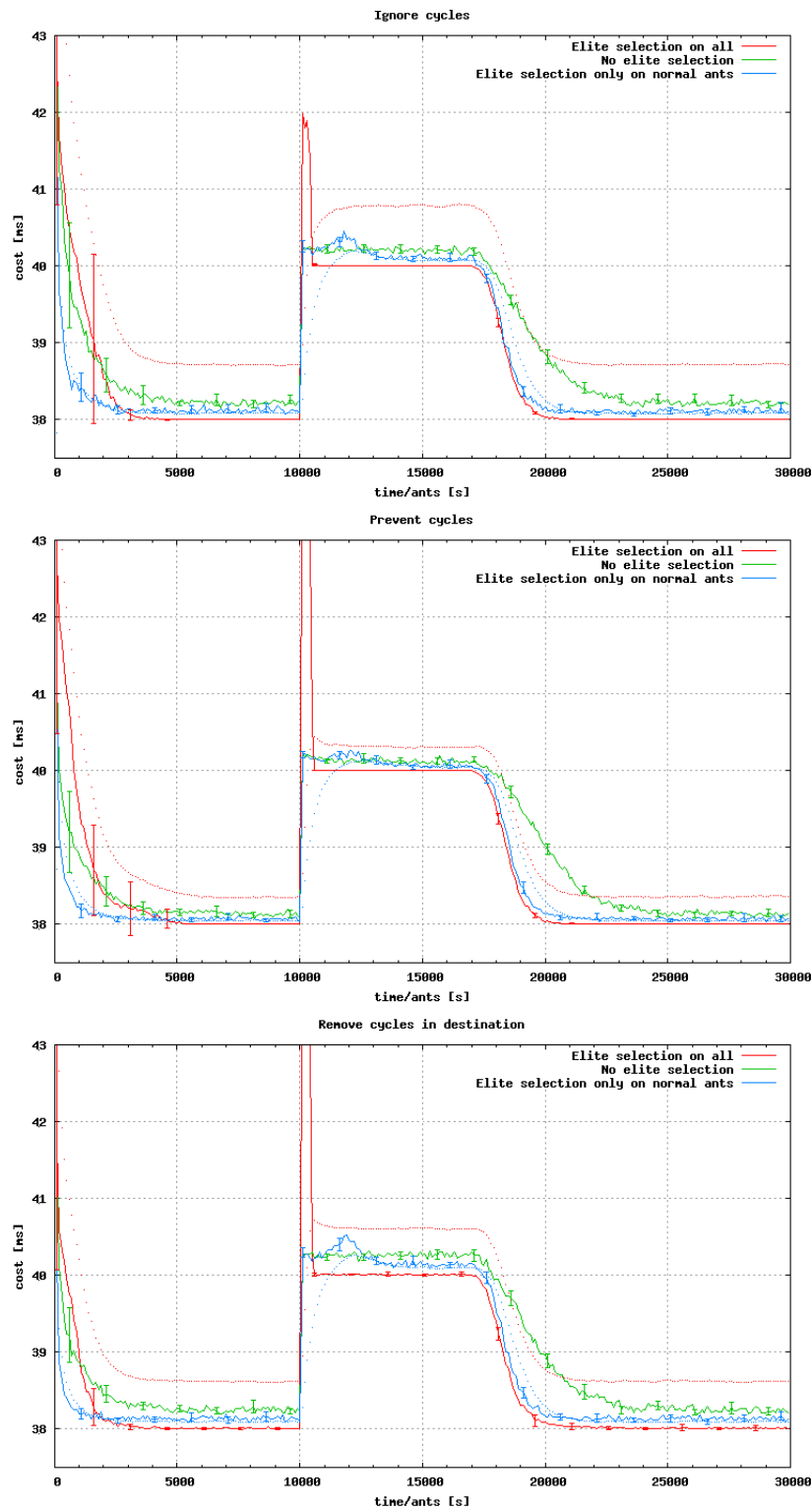


Figure 5.3: Comparison of different elite selection strategies and cycle treatments for the subpath CEAS. Costs between source and destination plotted with 95 % confidence intervals. Ignore cycles is shown in the top plot, prevent cycles in the middle plot, and remove cycles in the bottom plot.

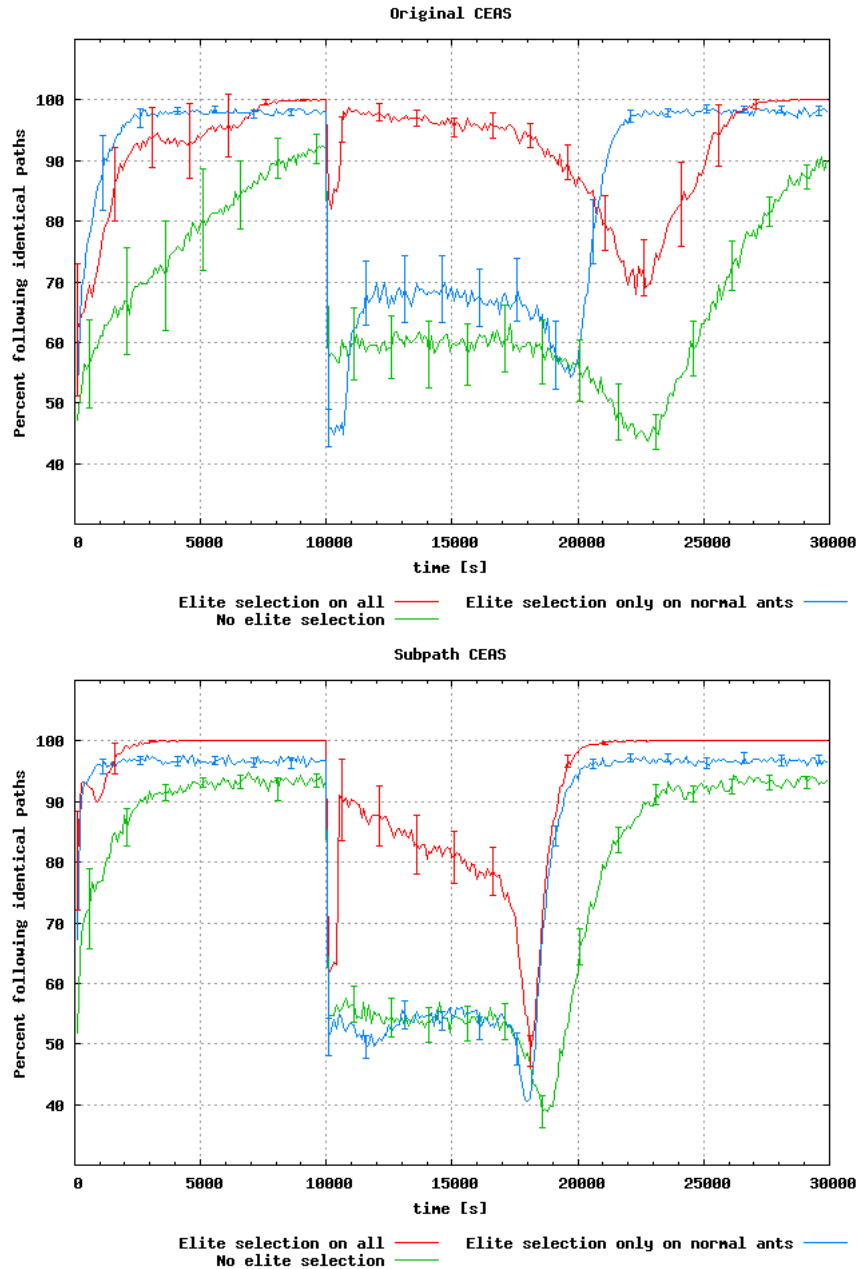


Figure 5.4: Path convergence for different elite selection strategies. A link failure occurs after 10 000 second resulting in two equally good paths, the link is restored 7000 seconds later. The values are sampled for each 100 second and are plotted with 95% confidence intervals. Original CEAS is shown in the top plot and subpath CEAS in the bottom plot.

are less apparent than in the original system. An interesting observation is the high cost peak for *elite selection on all* right after the link failure. This is probably caused by this strategy not leaving many pheromones on alternative paths after convergence. Unlike *elite selection on all* it was observed in the simulation output data that with *elite selection only on normal ants* or *no elite selection*, small pheromone values were left on alternative next best interfaces.

It was assumed that cycles could disturb the subpath algorithm, however different cycle treatment strategies seem not to affect the subpath system more than the original system. Still, since ignoring cycles may result in a lot of temperature calculations in the destination and because preventing cycles may possibly discard a lot of explorer ants, the third cycle treatment, *remove cycles in the destination* is used throughout this chapter if not stated otherwise.

Figure 5.4 shows the share of ants who followed identical paths sampled for each 100 second. It clearly shows how the new subpath CEAS more quickly chooses a path in the initial phase and more quickly adapts to network changes compared to the original CEAS. Notice where the systems reach 80 percent convergence, the subpath systems with elite selection seem to reach 80 percent convergence almost instantly. After the link failure (10000 seconds) there are two equally good paths and around 50 percent of the normal ants follow each. *Elite selection on all ants* indicates a much slower adaptation to this load sharing than *no elite selection* and *elite selection only on normal ants*. This is because the *elite selection on all ants* system first converges against one of the two best paths, hence discards most of the explorer ants that are following alternative paths. The increased focus on the first good path causes the system to overlook that there are actually two equally good paths after the failure.

5.3 SUBPATH CEAS VERSUS ORIGINAL CEAS

Based on the results in Section 5.2 the following three systems are compared:

- *Original CEAS with elite selection on all ants*
- *Original CEAS with elite selection only on normal ants*
- *Subpath CEAS with elite selection only on normal ants*

Cycles are removed in the destination for all systems.

The systems are compared with respect to a) *average cost*, b) *preferred path*, c) *pheromone updates* and d) *convergence*.

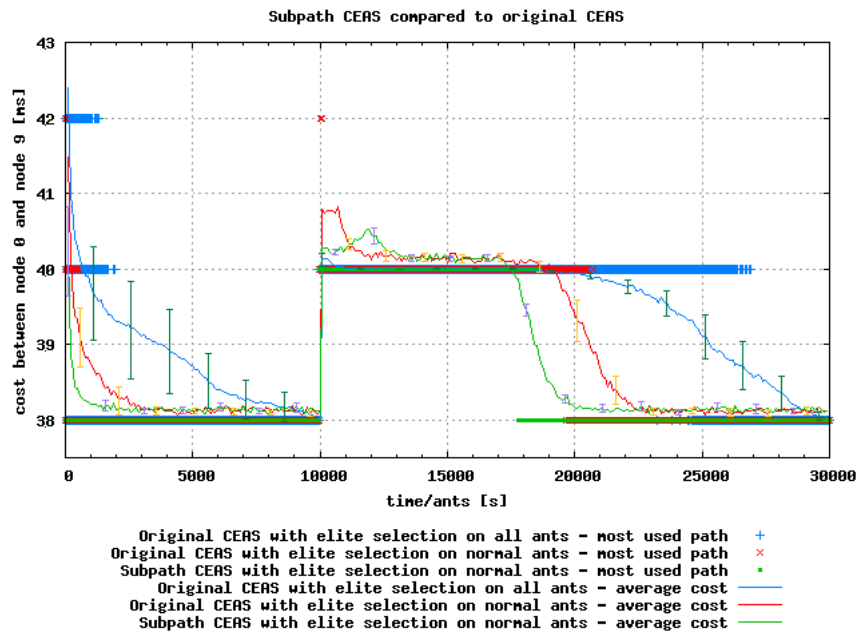


Figure 5.5: Comparison of *subpath CEAS* and *original CEAS*. Average costs between source and destination plotted with 95% confidence intervals, and cost of most popular path among the majority of the simulation replications.

Figure 5.5 shows the average cost between source and destination. The cost of the most popular path is also plotted, it is the preferred path among the majority of the simulation replications. Notice how the subpath ants more quickly choose the best path both in the initial phase and after the link restoration.

To give a better understanding of the observations, the pheromone values in the initial phase are plotted in Figure 5.6. The pheromone plots show the

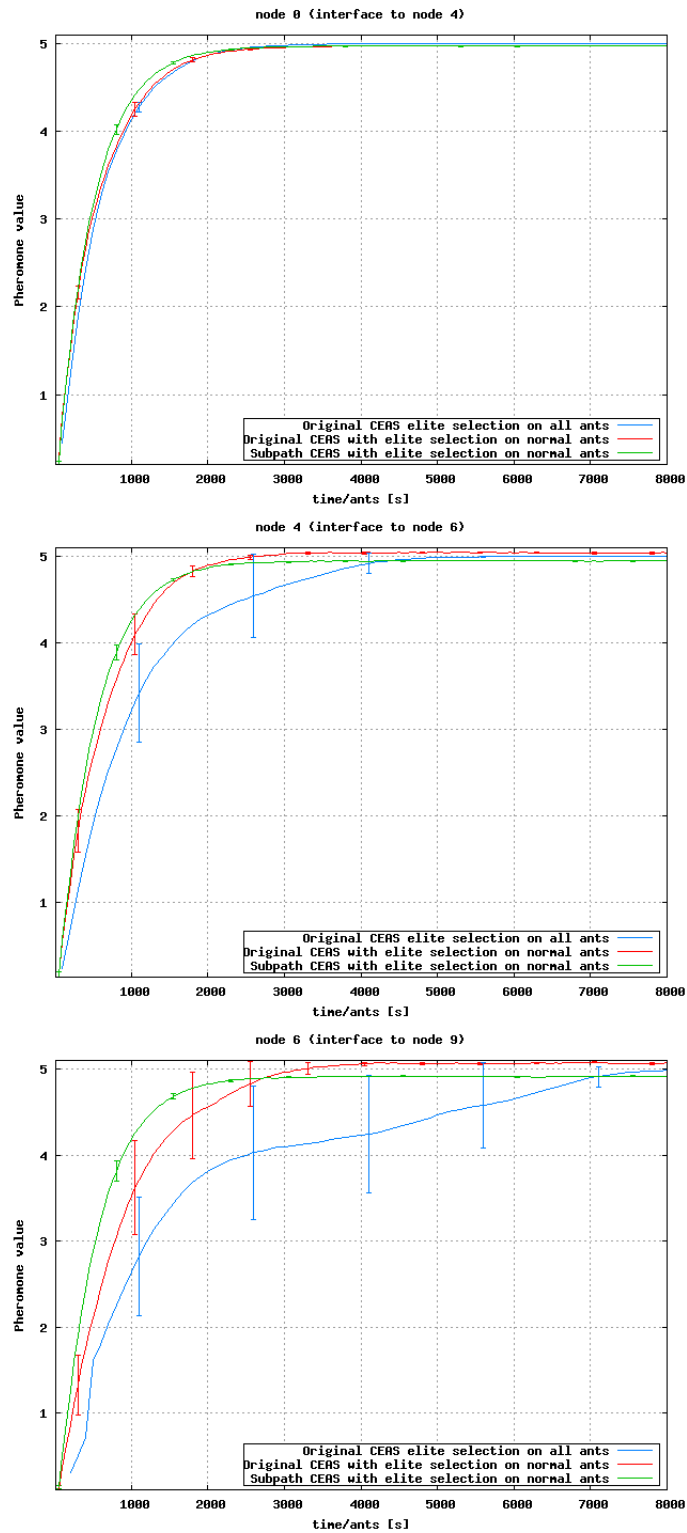


Figure 5.6: Pheromone values on the best path interface in the nodes that constitute the best path. Plotted with 95% confidence intervals.

pheromone value on the best interface in each node constituting the best path. It can be seen by the pheromone plots that the systems differ more in nodes close to the destination. Remember that the temperature and the pheromones in the original CEAS is *source-destination specific*, while in the subpath CEAS the temperatures are *node-destination specific* and the pheromones are *destination specific*. So said, in the original CEAS the pheromones in node six, that is close to the destination, are calculated with a temperature determined from paths between the source and the destination, while in the subpath CEAS they are calculated with a temperature determined from different paths between node six and the destination, hence node six sees a bigger difference between alternative paths.

To explain the difference in pheromone updates in intermediate nodes, the scenario described in Section 5.2 is used. The best path in this scenario is [0 4 6 9], with a cost of 3.8 ms. Following a next best interface in node six will result in a 0.2 ms higher cost. This is a change of 5 percent for the path between source and destination while it is a change of 11 percent for the subpath between nodes six and nine, hence node six sees a two times higher difference between the best and the next best paths with the subpath algorithm. One can say that the subpath CEAS results in a scaling of cost values that is more correct for what an intermediate node sees toward the destination. Similar when the link is restored, it represent a considerable improvement of the subpath from node six, and a smaller improvement of the main path measured from the source.

One could expect the fast convergence in nodes close to the destination to increase the convergence in preceding nodes, since the search space is decreased. However, in this topology the interfaces in preceding nodes benefit almost equally from the fast convergence in nodes closer to the destination, hence the pheromone convergence is not increased in preceding nodes. If the interfaces did represent very diverse paths, early convergence in nodes closer to the destination on one of the interfaces could increase convergence time for this interface, even though it might not be the best interface.

Reduced ant rate

The main goal of subpaths is to introduce destination specific pheromone values. This will reduce the pheromone tables and allow sharing of pheromones between ants from different sources going to identical destinations. The major drawback of the subpath CEAS is the increased amount of path evaluations and temperature calculations. However, results obtained so far show that the subpath CEAS performs better than the original CEAS, hence the ant rate can be reduced. Fewer ants will reduce the computational burden in both intermediate nodes and destinations, in addition to reduce the network load in terms of management packets. Figure 5.7 is identical to Figure 5.5 except that the ant rate in subpath CEAS, green curve, is reduced by 50 percent. The Figure shows that the subpath CEAS with reduced ant rate still converges faster than the original system. A higher average cost in the failure phase is also observed, possibly because there are two best paths at this stadium resulting in more ants following alternative paths.

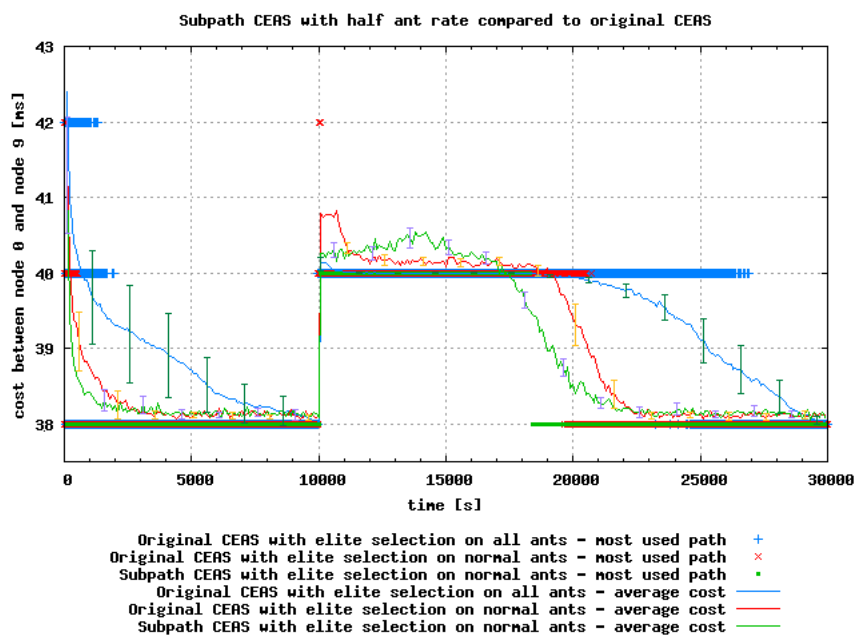


Figure 5.7: Original CEAS compared to subpath CEAS with reduced ant rate. Average cost between nodes 0 and 9 plotted with 95% confidence intervals, and most popular paths among the majority of the simulation replications.

5.4 PHEROMONE SHARING

The subpath CEAS makes pheromone sharing between ants with identical destinations possible. Results in Section 5.3 show improved performance with the new subpath CEAS using only one single source. In this section more sources are added to study the effects of pheromone sharing. It is expected that cooperation between sources will result in better performances, however possibilities are that the different sources will disturb each other and increase convergence times. Hopefully the performance will increase for each cooperating source, such that the ant rate and overhead can be reduced. In Section 5.4.1 pheromone sharing is examined in a small ten node topology. In Section 5.4.2 two cases in a nationwide 216 node topology are presented.

5.4.1 Ten node topology

Scenario:

Three more sources are added to the ten node topology, see Figure 5.8, all with node nine as their destination. After 10 000 seconds the link between nodes six and nine fails and 7000 seconds later it is restored. The outputs from the following three systems are compared:

- *Original CEAS*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
 - Init phase (all ants are normal): 10
- *Subpath CEAS without pheromone sharing*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
 - Init phase (all ants are normal): 10
- *Subpath CEAS with pheromone sharing*
 - Normal ant rate: 0.5
 - Explorer ant rate: 0.05
 - Init phase (all ants are normal): 20

All systems have elite selection only on normal ants and cycles removed in the destination. Notice that the ant rate is reduced by 50 percent when pheromone sharing is applied. (Reduced ant rate in the subpath CEAS was also investigated in Section 5.3).

Results:

Figure 5.9 shows the average cost and the cost of the most popular path between nodes zero and nine. The differences between pheromone sharing ants and original ants are most apparent in the restoration phase. Notice how the 4.0 ms path is used for a long time after the restoration by original ants, while the pheromone sharing ants quickly return to the 3.8 ms path. This is because all sources are cooperating in finding the new restored path, operating with a higher total ant rate through node six than a non-cooperating source alone. The quick detection of the restored path is also caused by a softer convergence during the failure phase. The plot in Figure 5.10 shows the *path convergence* between nodes zero and nine. The plot indicates an almost 50 percent load sharing and a quick response to link restoration with pheromone sharing. The original system has a slower convergence in the initial phase and almost 70 percent of the ants are following identical paths during the failure phase, although two paths are equally good at this stage. Thus when there is one best path, e.i. in the initial path search and in the restoration phase, the original algorithm tend to send a slightly larger share of ants on the best path, resulting in decreased focus on alternative paths.

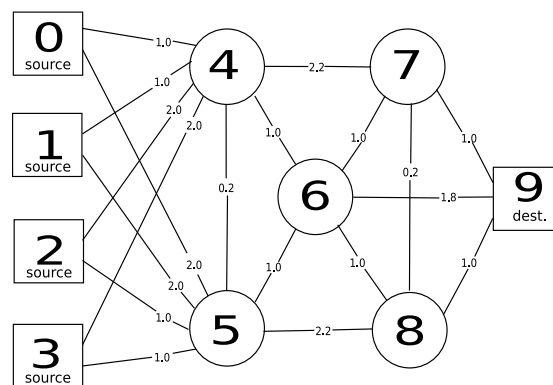


Figure 5.8: Ten node topology, four sources

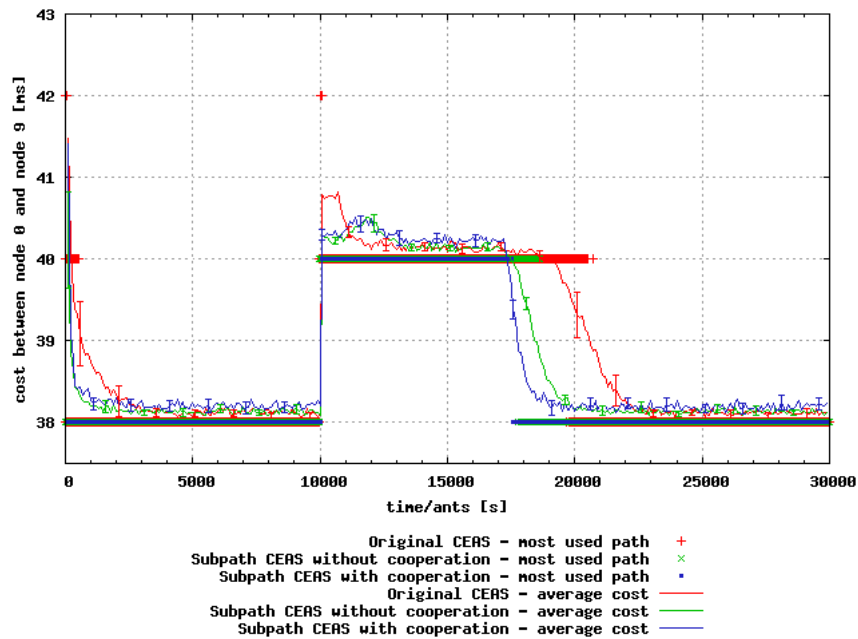


Figure 5.9: Original CEAS compared to subpath CEAS with and without pheromone sharing. Average costs between nodes 0 and 9 plotted with 95% confidence intervals, and preferred path among the majority of the simulation replications.

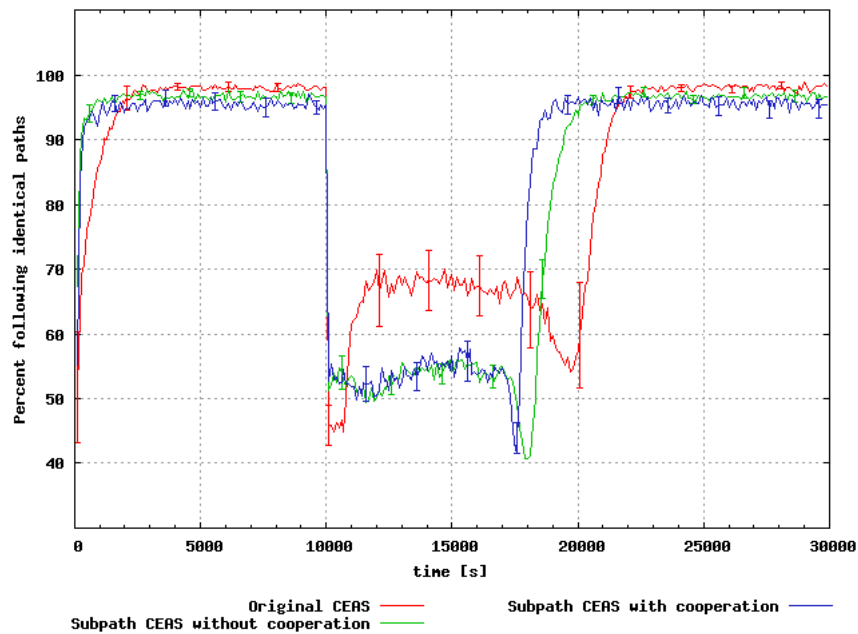
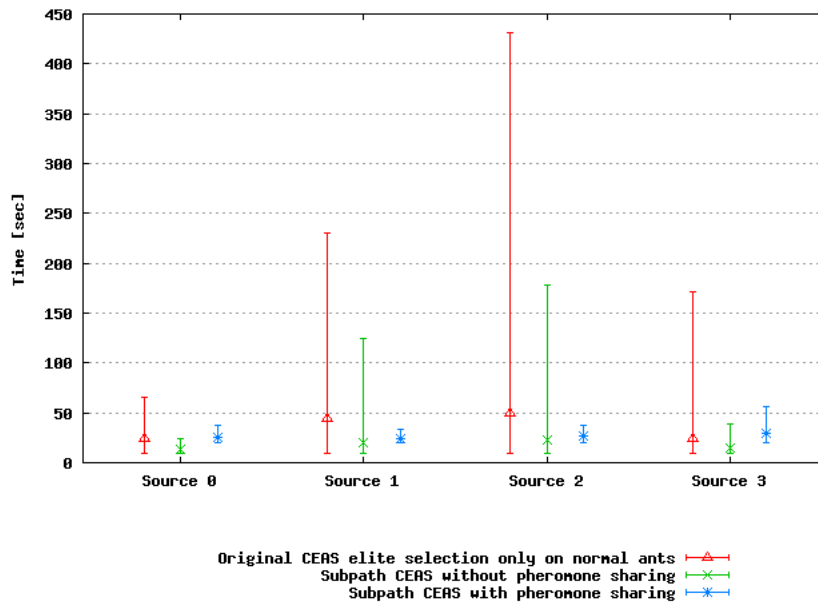
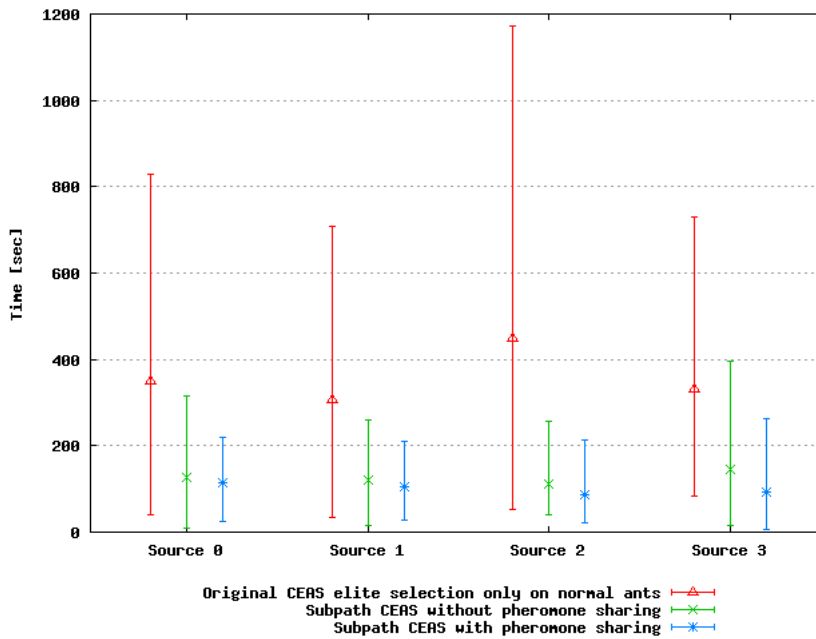


Figure 5.10: Path convergence for subpath CEAS with and without pheromone sharing compared to the original CEAS. A link failure occurs after 10 000 second resulting in two equally good paths, the link is restored 7000 seconds later. The values are sampled for each 100 second and are plotted with 95% confidence intervals.



(a) Init phase



(b) Restoration phase

Figure 5.11: Path detection time for each of the four sources, plotted with max/min values over 20 simulation replications. Top plot shows the initial path search and bottom plot shows the path detection time after a link restoration.

	<i>Convergence time [sec]</i> (min/max)	<i>Converged value [ms]</i> (min/max)	<i>Forward ants</i> (min/max)	<i>Backward ants</i> (min/max)	<i>Temperature calculations</i> (min/max)
Original CEAS	805 (100/3900)	3,82 (3,8/4,2)	887 (111/4291)	686 (98/3096)	1481 (187/6986)
Subpath CEAS without cooperation	254 (100/700)	3,81 (3,8/4,2)	281 (111/771)	272 (103/764)	1586 (606/4250)
Subpath CEAS with cooperation	331 (200/900)	3,8 (3,8/3,8)	152 (111/276)	152 (103/276)	751 (588/1524)

Table 5.2: Initial path convergence times. Values are averaged between all the four sources. Min/max values show the best case and worst case among all replications and all sources.

Figure 5.11 a) and b) show the *path detection time* for the initial phase and the restoration phase respectively. Fast path detection is especially important when that path is the only one suitable. When the link failure occurred, all systems did find the new best path within the ant interarrival time, this phase is therefore omitted in this comparison. A general observation in Figures 5.11 a) and b) is the high path detection times in the original CEAS worst cases, both for the initial path search and for the restoration phase. The results indicate that the subpath CEAS is twice as quick in finding the best path as the original CEAS in average. Notice that when the sources cooperate, the worst case times are better and more evenly distributed between the sources, indicating a more predictable system.

The next performance metric to be studied is the *convergence time*, here it is defined as the point in time when 80 percent of the normal ants follow paths with identical costs. The *convergence time* indicates when the system stabilizes, although it may not always converge against the best path, hence the system may converge to another and better value later. Table 5.2 shows *convergence time*, and corresponding overhead for the initial path search. The values are averaged over all four sources, worst case and best case values for all simulation replications are given in brackets. The number of ants and temperature calculations are measured at the time of convergence. The table shows an almost three times better *convergence time* for the subpath CEAS compared to the original system. Because the subpath CEAS converges three times faster, the number of temperature calculations performed when reaching 80 percent convergence is almost identical for the two systems. When four sources are cooperating with reduced ant rate, 80 percent convergence is reached a little later than without

	<i>Convergence time [sec] (min/max)</i>	<i>Converged value [ms]</i>	<i>Forward ants (min/max)</i>	<i>Backward ants (min/max)</i>	<i>Temperature calculations (min/max)</i>
Original CEAS	526 (100/1000)	4.0	579 (110/1100)	126 (10/362)	653 (110/1329)
Subpath CEAS without cooperation	100 (100/100)	4.0	110 (110/110)	110 (110/110)	558 (548/567)
Subpath CEAS with cooperation	103 (100(200))	4.0	57 (55/110)	57 (55/110)	286 (270/555)

Table 5.3: Convergence times after a failure. Values are averaged between all the four sources. Min/max values show the best case and worst case among all replications and all sources.

cooperation, still more than two times faster than the original CEAS. The overhead is considerably reduced with the cooperating subpath CEAS. Compared to the original CEAS it only needs 1/5 of the ant packets and 1/2 of the temperature calculations. Notice that in its worst case the original CEAS need 13 times as many ant packets to reach 80 percent convergence than the subpath CEAS with pheromone sharing, and that the latter system never misses the best path. One should also notice that almost all packets are returned as backward ants in the subpath system, i.e. elite selection does not reduce the overhead in terms of backward ants during the convergence time.

Table 5.3 shows *convergence time* and corresponding overhead after the link failure. The convergence times are now redefined as the point in time where 80 percent of the ants follow one of the theoretical best paths after the failure in link 6-9, e.i. the converged value will always be 4.0 ms. A five times faster convergence is observed for the subpath systems compared to the original system. With pheromone sharing the subpath system only need 1/6 of the ant packets and less than 1/2 the temperature calculations to reach 80 percent convergence compared to the original CEAS. Notice how elite selection discards backward ants in the original system, and not at all in the subpath systems. In extreme cases all normal ants are discarded. If elite selection were performed on explorer ants as well, no ants would have been returned and to some extent explains the reduced performance of *elite selection on all ants*, studied in Section 5.2.

Table 5.4 shows *convergence time* and corresponding overhead after the link is restored. The convergence time is now defined as the time to 80 percent of the normal ants follow the restored best path after the restoration, e.i. the con-

	<i>Convergence time [sec] (min/max)</i>	<i>Converged value [ms]</i>	<i>Forward ants (min/max)</i>	<i>Backward ants (min/max)</i>	<i>Temperature calculations (min/max)</i>
Original CEAS	3635 (2500/5400)	3.8	3999 (2750/5940)	2883 (1530/4862)	6518 (4030/10262)
Subpath CEAS without cooperation	1956 (1600/2300)	3.8	2152 (1760/2530)	2152 (1760/2530)	12750 (10405/14342)
Subpath CEAS with cooperation	1085 (800/1300)	3.8	597 (440/715)	597 (440/715)	3612 (2634/4412)

Table 5.4: Time to convergence of a restored best path. Values are averaged between all the four sources. Min/max values show the best case and worst case among all replications and all sources.

verged value will always be 3.8 ms. A more than three times faster convergence is observed for the pheromone sharing ants compared to the original CEAS, and only 1/5 of the ant packets and 1/2 of the temperature calculations are needed to reach 80 percent convergence. This is mainly because the restored path represents a more significant improvement for nodes six and four than in the original system. This is a property of the subpath algorithm and was explained in Section 5.3. The results from this phase are also explained by the benefit of pheromone sharing. The cooperating sources operate with a higher total ant rate than each source alone. The third aspect explaining the fast return to the restored path is a softer convergence in the preceding phase.

Conclusion: To summarize, the subpath CEAS with pheromone sharing outperforms the original CEAS both with respect to performance and overhead. The *convergence times* are in average reduced by 60-80 percent for all three phases. The overhead in terms of ant packets is reduced by 80 percent, and the temperature calculations are reduced by almost 50 percent. Note that values in the tables are average convergence times of all the sources and the overhead is per source.

In the scenario presented in this section the subpath CEAS with pheromone sharing turned out to be a win-win alternative compared to the original CEAS, i.e. better performance and reduced overhead. However, one should remember that this scenario and topology was nearly ideal for the cooperation approach. In the next section a more realistic network with sources located in different areas are examined.

5.4.2 Nationwide network

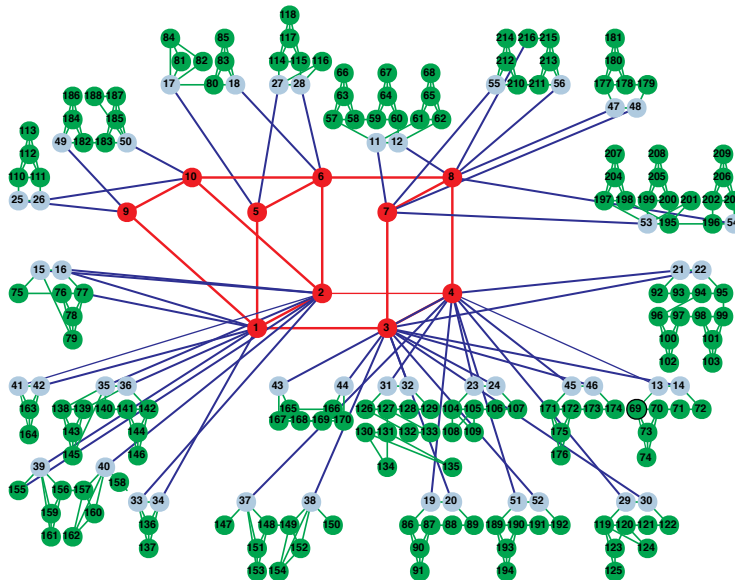


Figure 5.12: Nationwide communication network with 216 nodes. (Figure adapted from [Heegaard and Fuglem, 2006])

In this section case studies are carried out based on a 216 node network topology extracted from a major Norwegian Internet provider. It consists of 10 core routers in a partly meshed topology, a ring based edge network with a total of 46 routers, and a dual homing access network with 160 access routers. The relative transmission capacities are 1, 1/4 and 1/16 for core, edge and access links respectively. The average number of hops between the access routers is 6.37. This topology was chosen to provide a realistic setting for the new sub-path CEAS with pheromone sharing.

Two different cases are examined, those are:

- *CASE I: 2+1 sources* - Two nodes start their path search simultaneously. A third node starts its search at a later point in time.
- *CASE II: Eight sources* - Eight sources start their search simultaneously

CASE I: 2+1 sources**Scenario:**

The following three systems are compared in this case:

- *Original CEAS elite selection on all ants*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
 - Elite selection: On all ants
 - Cycle treatment: Ignore cycles
- *Original CEAS elite selection only on normal ants*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
 - Elite selection: Only on normal ants
 - Cycle treatment: Remove cycles in destination
- *Subpath CEAS with pheromone sharing (Cooperation between sources)*
 - Normal ant rate: 0.5
 - Explorer ant rate: 0.05
 - Elite selection: Only on normal ants
 - Cycle treatment: Remove cycles in destination

Notice that two versions of the original CEAS system are included to see if results regarding elite selection strategies are similar to the results obtained for the ten node topology.

In this first case two access routers, nodes 75 and 84, start searching for the best path to node 74 simultaneously. After 20 000 seconds a new access router, node 110, starts its search for node 74. There are now pheromones in the network, left by ants from nodes 75 and 84, which can be utilized by node 110. The scenario is created to see how sources in different access networks with different entries in the core network, although located relatively close, can benefit from cooperation. Examinations on how a new connection can benefit from the pheromones already placed by other sources are also included. It is expected from observations so far that the subpath algorithm with pheromone sharing will perform better than the original algorithm. However, this is not obvious since there are only two sources cooperating with a total ant rate equal to each non-cooperating source.

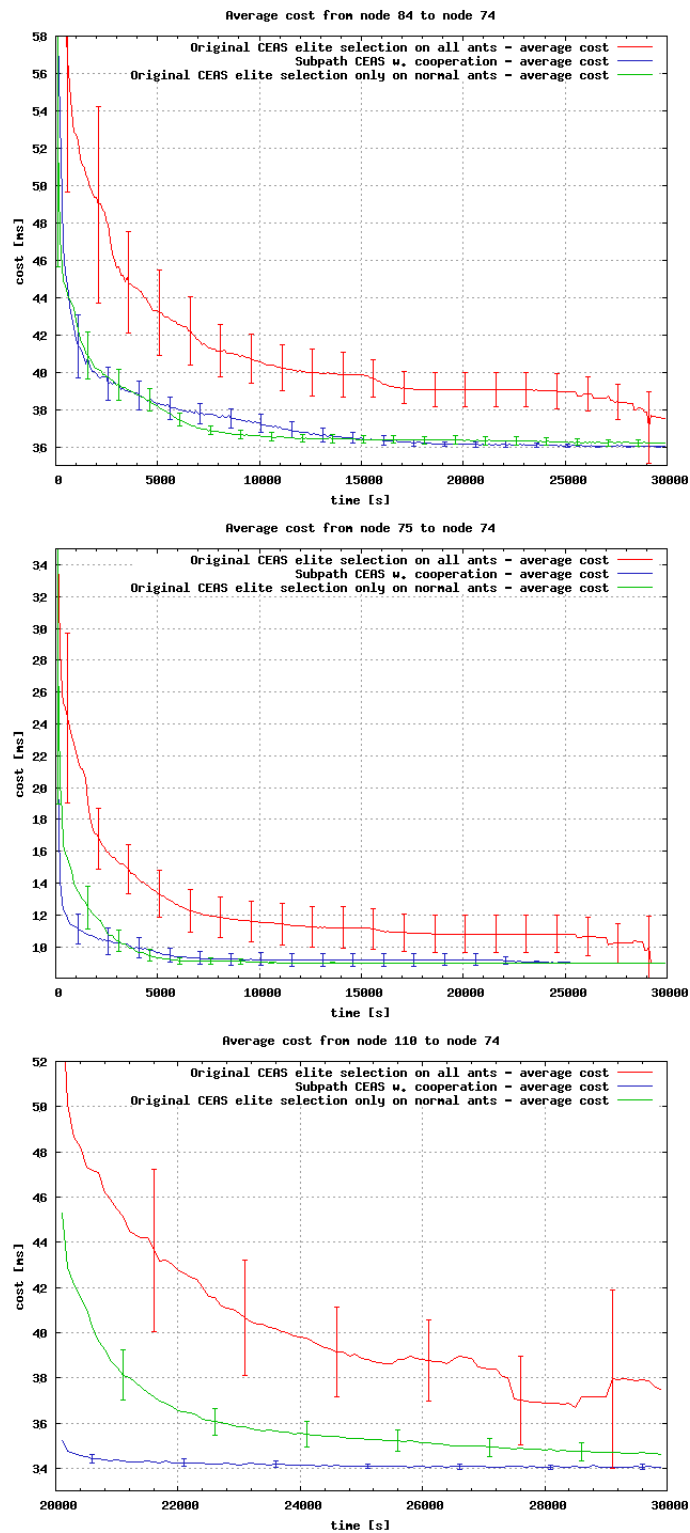


Figure 5.13: Average costs from the three sources plotted with 95% confidence intervals. In the subpath CEAS with pheromone sharing the ant rate is reduced by 50 percent. Notice that the search from node 110 (bottom plot) starts 20 000 seconds later than the other two sources.

Results:

Figure 5.13 shows the average cost from each of the three sources to the destination. The original CEAS with elite selection on all ants clearly under performs compared to the other two systems, strengthening the theories from Section 5.2 regarding elite selection strategies. The cooperative sources have the benefit of pheromone sharing, however operate with 50 percent reduced ant rate. Despite fewer ants from each source it performs almost equally well as the original CEAS with elite selection only on normal ants. Observations of node 110 show that it really benefits from the pheromones already left by sources in nodes 75 and 84.

CASE II: Eight sources

In case I it was observed that the original CEAS performed better with elite selection only on normal ants than with elite selection on all ants. This strengthens the observations in Section 5.2 and only this elite selection strategy is applied in the following.

The following four systems are compared in case II:

- *Original CEAS*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
- *Subpath CEAS without pheromone sharing*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
- *Subpath CEAS with pheromone sharing*
 - Normal ant rate: 1.0
 - Explorer ant rate: 0.1
- *Subpath CEAS with pheromone sharing, reduced ant rate*
 - Normal ant rate: 0.5
 - Explorer ant rate: 0.05

All systems use elite selection only on normal ants and cycles are removed in the destination.

Scenario:

Eight sources located in access routers evenly distributed in the network are simultaneously searching for the best path to destination node 74. Two link failures in the core network occur after 10 000 seconds and is restored 7000 seconds later, the failing links are 4-8 and 1-3. There is a question how nodes with very different locations will benefit from pheromone sharing. Some of the nodes, mostly core nodes, will experience increased ant rates probably resulting in a faster convergence of pheromones. It is however possible that the different sources will disturb each other and some sources may experience reduced performances.

Results:

The average costs are plotted in Figure 5.14, one diagram for each of the eight sources. In general the original system seems to under perform for all the eight sources compared to the subpath systems. The cooperation through pheromone sharing seems to perform better for six of the eight sources. The two nodes closest to the destination, nodes 91 and 125, converge faster without pheromone sharing in the initial phase, and are probably disturbed by the other sources. When the links fail, the original CEAS has a higher cost peak than the subpath CEAS. This was also observed in Figure 5.2 for this system, and explained by this system's strict elite criterion discarding more ants at the point of failures. For a better visualization, without too many close or overlapping curves, the results of the fourth system, *subpath CEAS with reduced rate*, was omitted in Figure 5.14, however it will be included in the following performance comparisons.

The initial phase (0-10 000 seconds) is investigated in detail with respect to *path detection time*, *convergence time* and *converged value*. The *path detection time* is redefined as the time when the best path was found, although not necessarily the theoretical best path. The path detection time for each of the four sources are plotted in Figure 5.15. The performance of the different systems vary, however the original CEAS clearly shows a longer *path detection time* for almost all sources both in average and in its worst case. The average *path detection time* over all sources is given in Table 5.5. The table shows a twice as fast path detection for the subpath CEAS with pheromone sharing compared to the original CEAS. The values in Table 5.5 are colored to indicate the systems

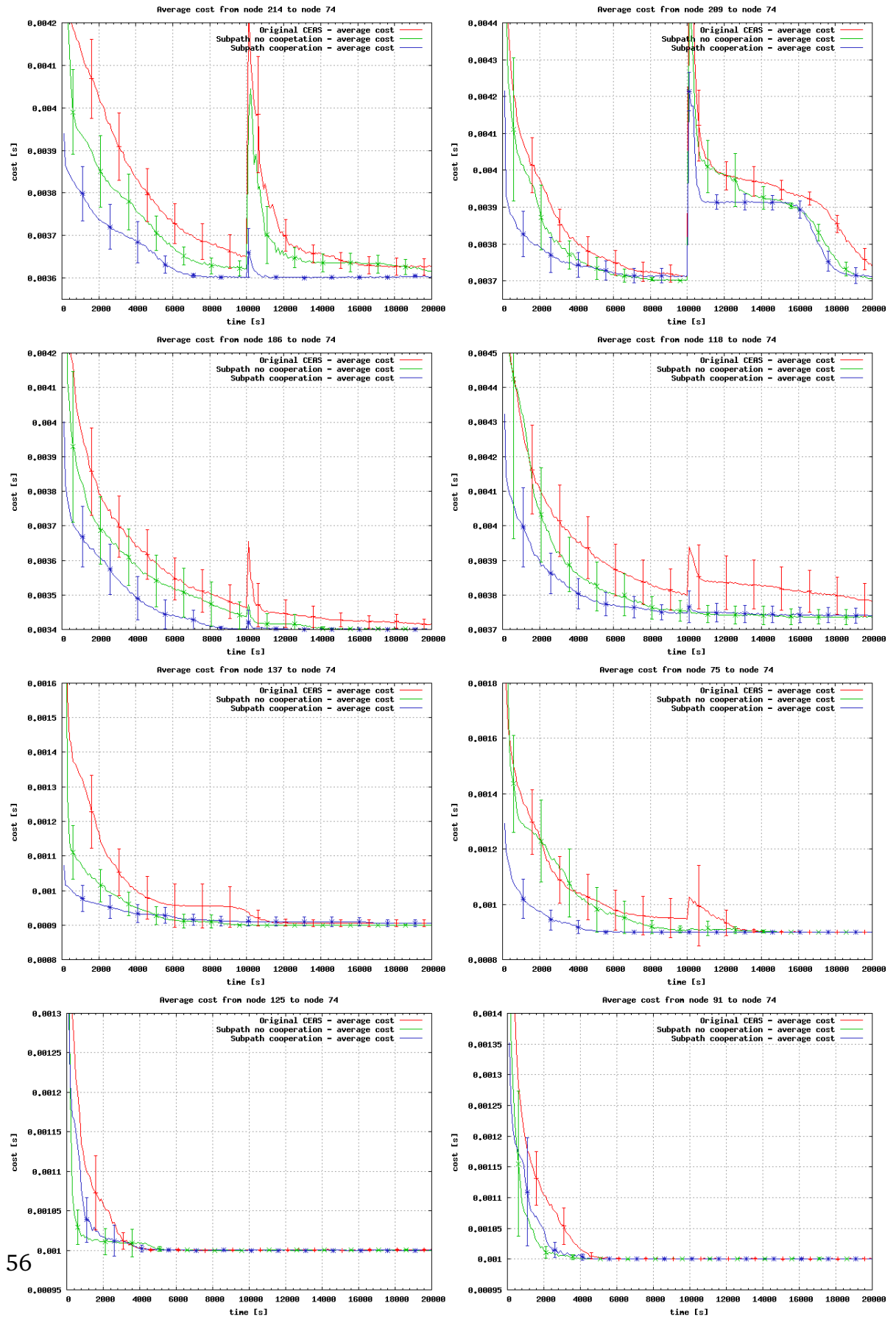


Figure 5.14: Average cost for each of the eight sources, plotted with 95% confidence intervals.

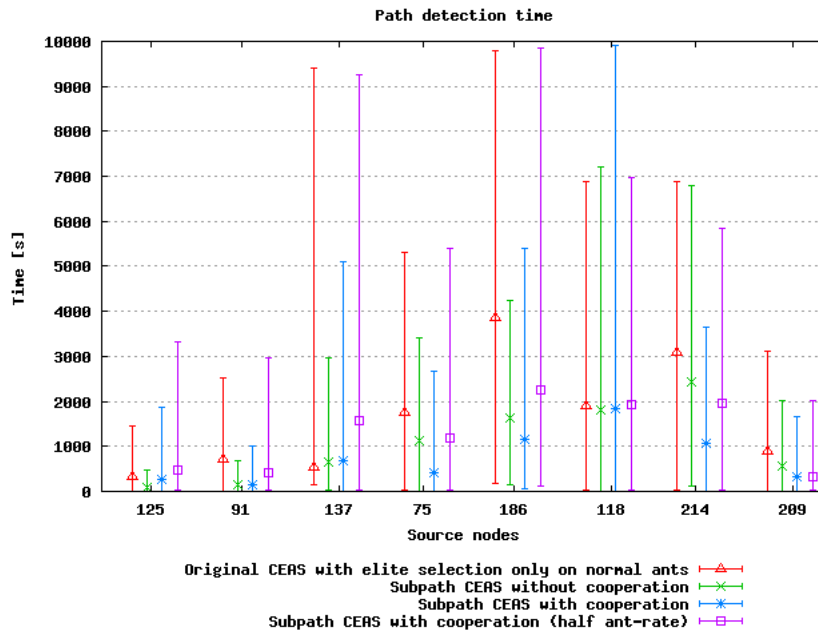
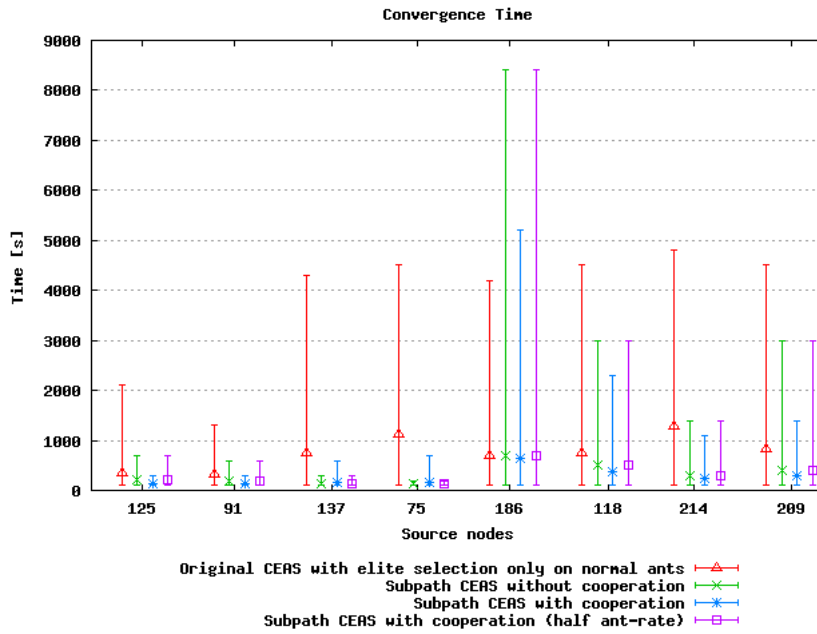


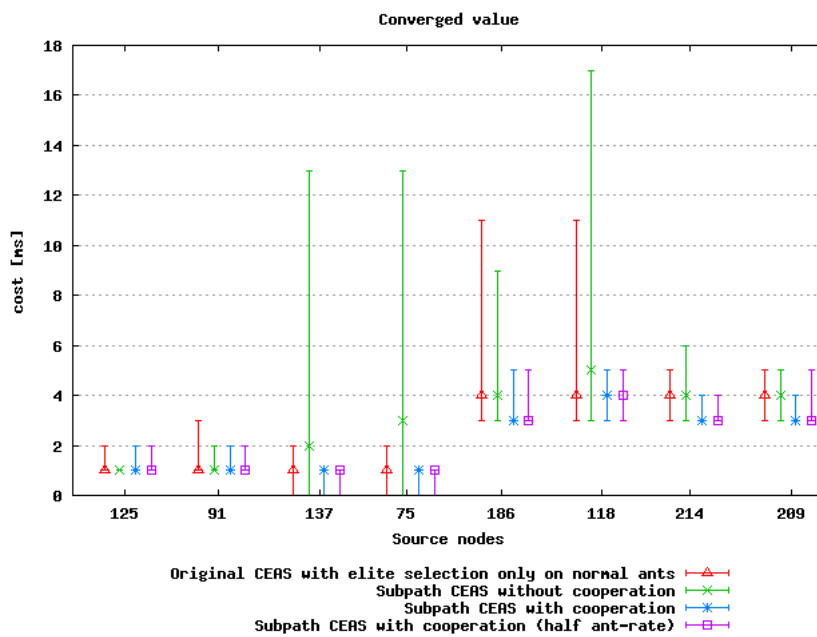
Figure 5.15: Path detection time for each of the eight sources. Average values plotted with max/min over 20 simulation replications.

performance relative to the three other systems. The brackets are the min/max values over all simulation replications and all sources.

The *convergence times* and the *converged values* for each of the eight sources are depicted in Figure 5.16 a) and b) respectively. In general a longer *convergence time* is observed for the original CEAS compared to the three subpath systems. The differences between the subpath systems with and without pheromone sharing are not that obvious in the figure, however the average *convergence time* given in Table 5.5 is more than two times shorter with pheromone sharing, even with 50 percent reduced ant rate. Looking at both Figures 5.16 a) and b), a fast *convergence time* and a poor *converged value* is observed for nodes 75 and 137 in the subpath CEAS without pheromone sharing. This implies that the sources have a very fast convergence, although the convergence misses the good paths. The plots only show the first converged value, and hopefully the sources converge to a better value at a later point in time. To examine this, the path convergence is plotted for each of the eight sources in Figure 5.17. Investigating the plots it is seen how 80 percent convergence is reached several times for nodes 75 and 137 before they finally stabilize.



(a)



(b)

Figure 5.16: Convergence time and converged value for each of the eight sources. Average values plotted with max/min over 20 simulation replications.

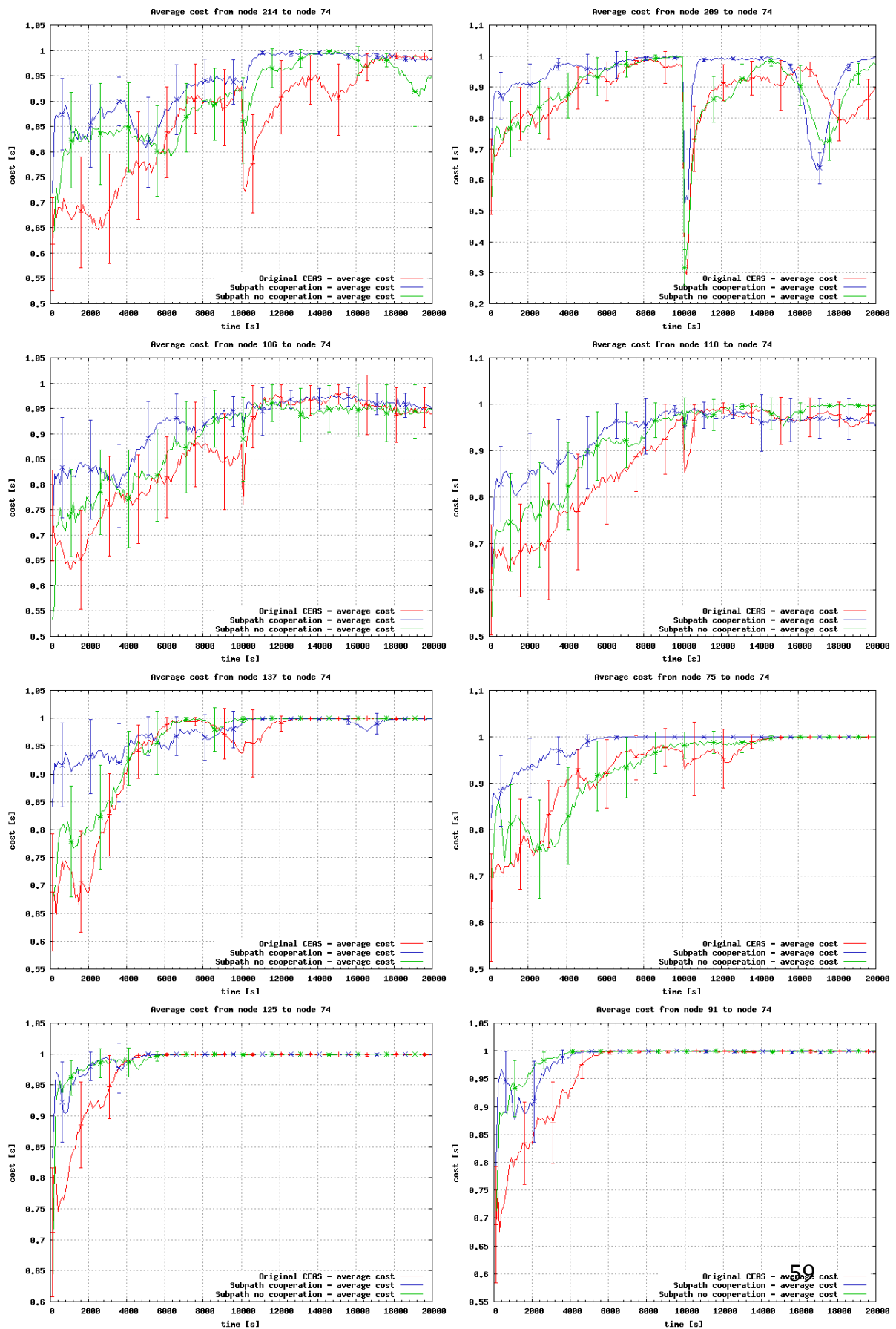




Figure 5.17: Path convergence for each of the eight sources, plotted with 95% confidence intervals.

The overhead in terms of *temperature calculations*, *forward ants* and *backward ants* given in Table 5.5 are measured at the time of convergence. The temperature calculations are significantly reduced by applying pheromone sharing and are only slightly higher than for the original CEAS. With pheromone sharing and a reduced rate, overhead in terms of ant packets are reduced by more than 70 percent. Studying the *path detection time* and the *convergence time* it is seen that the systems in average converge before the best path is found. This implies a premature convergence and the final convergence may be of a better path.

Conclusions:

In this scenario, regarding the performance metrics *path detection time* and *convergence time*, the benefits of introducing pheromone sharing in the subpath system are greater than going from the original system to the subpath system. It was also observed that the subpath CEAS without pheromone sharing did sometimes converge against poor cost values and the temperature calculations for this system were very high. However the poor *convergence values* were eliminated by introducing pheromone sharing and the temperature calculations were significantly reduced. In Case II the convergence was observed to be less smooth than in earlier observations, see Figure 5.17, thus the convergence times in Table 5.5 are likely of a premature convergence. Despite a much shorter convergence time of systems with pheromone sharing a better converged value was achieved. For a brief summary of all results presented in this chapter, see Chapter 6.

	Path detection time [sec]	Best path found [ms]	Convergence time [sec]	Converged value [ms]	Temperature calculations	Forward ants	Backward ants
Original CEAS	1631 (10/9797)	2.30 (0.9/3.9)	764 (100/4800)	2.93 (0.9/11.7)	1346 (84/8498)	842 (111/5281)	593 (3/3709)
Subpath CEAS without cooperation	1062 (10/7199)	2.28 (0.9/3.8)	650 (100/6500)	3.16 (0.9/17.9)	11 443 (691/130 819)	716 (111/7151)	635 (10/6584)
Supath CEAS with cooperation	737 (10/9908)	2.28 (0.9/3.8)	267 (100/6200)	2.51 (0.9/5.2)	1518 (1065/2959)	294 (110/5724)	263 (85/5285)
Subpath CEAS with cooperation (50 % reduced ant rate)	1258 (20/9852)	2.28 (0.9/3.8)	322 (100/8400)	2.58 (0.9/5.2)	1695 (457/12023)	178 (56/4621)	155 (34/4257)

 Best:
 Second best:



 Second worst:
 Worst:

Table 5.5: Performance and overhead at time of initial convergence. Brackets are min/max values over all simulation replications.

CONCLUDING REMARKS AND FUTURE WORK

6.1 CONCLUDING REMARKS

With the introduction of new routing requirements, brought forth by a wide range of communication intensive, real-time multimedia applications, more sophisticated routing techniques are required in today's communication networks. The Cross Entropy Ants System (CEAS) is an adaptive, robust and distributed routing and management system based on swarm intelligence. The CEAS is performing stochastic routing with fast restoration on link failures. In this project a new version of CEAS is presented. The new system, denoted *subpath CEAS*, applies pheromone sharing between sources with identical destinations, in order to reduce overhead and increase scalability.

Elite selection, first introduced in [Heegaard et al., 2004], are further examined both for the new subpath system and the original system. By ensuring that insignificant paths are not processed, elite selection reduces overhead and increases the focus on good paths. Results from the investigations carried out in this work clearly indicate a better performance for *elite selection only on normal ants* compared to *elite selection on all ant types*. This is explained by the strategy's benefit of elite selection's focus on good paths while it simultaneously keeps a wider search space by always processing explorer ants. An observation, that was anticipated, is that elite selection does not discard many backward ants in the subpath system, however elite selection is still efficient because of improved performance.

Performance wise the new subpath system shows good results compared to the original system, both in a small network with ten nodes and in a more realistic communication network with 216 nodes. Simulation results from the

ten node network indicate at least a two times faster convergence compared to the original CEAS in all phases, e.i. initial path search, when a link fails and when a link is restored. In the 216 node network only 15 percent improved convergence time was observed, however when applying pheromone sharing and cooperation between the sources, the subpath CEAS converged more than twice as fast compared to the original system. The better performance of the subpath system is mainly explained by the better scaling of pheromone updates in intermediate nodes. This is because the subpath CEAS maintains individual path costs and temperatures toward a destination for each intermediate node.

In all swarm systems there is a tradeoff between performance and management overhead (number of ant packets). In the subpath system the packet rate can be reduced mainly because of two reasons; 1) *Improved performance* and 2) *Cooperation between sources with identical destinations*. Since the subpath system converges faster the packet rate can be reduced and still keep an adequate performance. When sources cooperate, the total ant rate through many junctions are increased, hence the ant rate per source can be reduced. When measuring overhead in terms of management packets at the time of convergence, the subpath CEAS indicates 60 percent reduction of management packets during the convergence time in the 216 node topology. When applying pheromone sharing and reducing the ant rate from each source by 50 percent, almost 80 percent reduction in management packets is achieved. A better converged value was also achieved by pheromone sharing.

The major drawback of the subpath system is the increased number of temperature calculations. In the ten node topology, because of fast convergence, the subpath system with pheromone sharing actually showed a reduction in temperature calculations at the time of convergence by almost 50 percent. In the 216 node topology the subpath CEAS with pheromone sharing and the original CEAS needed an approximately equal amount of temperature calculations to reach 80 percent convergence. This is still a satisfying result for the subpath CEAS because other overhead metrics such as pheromone tables and management packets are significantly reduced. Ongoing work addresses new path evaluations and performance functions in CEAS which potentially will reduce the computational overhead in destination nodes.

6.2 FUTURE WORKS

Increased scalability because of reduced routing tables is achieved by the subpath CEAS. Future works include testing the subpath CEAS in larger scenarios with many connections. Traffic load should be included to see if cooperation increases the possibility of congestions. It might be interesting to study the subpath CEAS in a topology with very diverse paths. By this the effects of decreased search space can be investigated, because nodes close to the destination tend to converge faster. An increased convergence is expected in such a topology, however possibilities are for a premature convergence in nodes close to the destination.

Future works also include applying the subpath algorithm to other CEAS related works. Self-tuned rate control is introduced in [Heegaard and Wittner, 2006]. Self-tuned rate control can be used to increase the ant rate when failures occur, or reduce it when path searches converge. A self-tuned rate control is likely to be efficient in different CEAS applications and should be included in the subpath system. By such a strategy the overhead can be reduced by decreasing the ant rate when connections converge. The use of CEAS to find virtual connections realized by Multiprotocol Label Switching (MPLS) was examined in [Hesby et al., 2004]. If pheromone sharing is applied a new connection can utilize from pheromones placed by mature connections, and by this establish new vertical connections very fast.

In this work the subpath system did find routes that were optimized on only one additive constraint. This is not adequate for many emerging Internet applications which need support for diverse traffic. Finding paths that satisfies several constraints introduce challenging problems. Many multi-constrained path selection problems are NP-complete and cannot be resolved in polynomial time [Wang, 1999]. The complexity and deployment of QoS-routing still need to be solved with respect to complexity and scalability. CEAS is a candidate to solve such complex routing problems and the subpath system should be applied in finding routes that are subject to multiple constraints. In addition to select routes that can meet certain Quality of Service (QoS) requirements, utilization of different network resources should be considered. In [Wittner et al., 2003b]

CEAS is applied in finding resource paths conforming to a set of different search profiles. The subpath system should be investigated on such composite routing problems, applying constraints that may be both *path-constrained* (additive or multiplicative) or *link-constrained* (concave).

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APPENDIX **A**

SOURCE CODE

The following three Network Simulator 2 (NS2) routing modules have been used in this project:

1. *VebCEantNoSubpath* - Implementation of the original CEAS with additional features for cycle treatment and elite selection.
2. *VebCEantNoSharing* - Implementation of the subpath CEAS with individual pheromone values for each connection.
3. *VebCEantSharing* - Implementation of the subpath CEAS with destination specific pheromones and pheromone sharing between sources.

The modules can be accessed through CVS at Centre for Quantifiable Quality of Service in Communication Systems (Q2S)¹ or merged into NS2 from the enclosed patch file.

Q2S's CVS

CEAS code base including the new modules is available from Q2S's CVS on request. The locations of the new modules in the CVS directory tree are shown in Listing A.1.

Listing A.1: CVS directory three

```
| -CEants_ns-allinone-2.30
| ----ns-2.30
| -----swarm
| -----common
| -----VebCEantNoSharing
| -----VebCEantNoSubpath
| -----VebCEantSharing
```

¹Q2S - the Centre for Quantifiable Quality of Service in Communication Systems is a Norwegian Centre of Excellence at the Norwegian University of Science and Technology in Trondheim (www.q2s.ntnu.no)

Patch for NS2 version 2.30

The CEAS code base including the new modules can be merged from a patch to NS2 version 2.30. The patch file `ant-like_agents_for_ns2-2.30_2007-06-22.patch` was submitted as an attachment to this thesis on the DAIM thesis system at the Norwegian University of Science and Technology (NTNU) (daim.idi.ntnu.no).

The patch can be merged into the NS2 sources by the following command:

```
patch -p[n] < ant-like_agents_for_ns2-2.30_2007-06-22.patch
```

where `n` is the number of leading components to strip from the path.