A Model Based Approach to Reachability Routing

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Abstract

Current directions in network routing research have not kept pace with the latest developments in network architectures, such as peer-to-peer networks, sensor networks, ad-hoc wireless networks, and overlay networks. A common characteristic among all of these new technologies is the presence of highly dynamic network topologies. Currently deployed single-path routing protocols cannot adequately cope with this dynamism, and existing multi-path algorithms make trade-offs which lead to less than optimal performance on these networks. This drives the need for routing protocols designed with the unique characteristics of these networks in mind.

In this paper we propose the notion of reachability routing as a solution to the challenges posed by routing on such dynamic networks. In particular, our formulation of reachability routing provides cost-sensitive multi-path forwarding along with loop avoidance within the confines of the Internet Protocol (IP) architecture. This is achieved through the application of reinforcement learning within a probabilistic routing framework. Following an explanation of our design decisions and a description of the algorithm, we provide an evaluation of the performance of the algorithm on a variety of network topologies. The results show consistently superior performance compared to other reinforcement learning based routing algorithms.

1 Introduction

The next generation of network technologies such as sensor networks, peer-to-peer networks, ad-hoc wireless networks, and overlay networks present challenges that have previously not been witnessed in the Internet infrastructure. These networks operate on large topologies which are highly dynamic in terms of changes in cost and connectivity. In these contexts, single-path routing protocols, the mainstay on current network topologies, suffer from either route flap or temporary loss of connectivity when the primary path fails. In addition, these protocols do not make effective use of the graph connectivity between a sender and receiver in order to improve performance. Effectively, addressing these unique requirements demands routing protocols that can address a number of novel performance metrics.

Historically, routing algorithms evolved from networks where the only parameters available for making routing decisions were source and destination addresses. 1 These parameters by themselves

1While source routing is still prevalent in some data center networks, and was present in the early Internet, it is not scalable for graphs of arbitrary diameter.
do not have sufficient discriminative capability to avoid loops. Hence optimality criteria were added to the routing formulation to eliminate loops leading to single-path routing, which no longer meets the needs of the next generation of network technologies.

To address the needs of emerging network domains, in this paper we attempt to build a routing protocol with the following characteristics. First, the routing protocol should be capable of converging to a solution even in highly dynamic environments merely with local information i.e., the protocol does not require any global knowledge of the topology. Second, to maximize the bandwidth (and connectivity) between any pair of nodes, the routing protocol should route along multiple paths between them. Third, the routing protocol should route as efficiently as possible by selecting routes in inverse proportion to their expected path cost. Fourth, the protocol should avoid loops as much as possible and guarantee not to get stuck in loops – the emphasis is on loop avoidance rather than loop elimination. Finally, to be of maximum practical value, the protocol should work within the confines imposed by the Internet Protocol (IP) specification, including its header fields which only permit a source and destination. As mentioned before, source routing has been tried in IP networks, but was discarded due to security issues, the lack of space in the IP header to support full source routing for all nodes, as well as its lack of scalability in large networks.

Note that these requirements place conflicting demands on routing protocol design. Different algorithms make differing trade-offs in this multi-constraint space. For instance, distance vector and link state algorithms achieve loop elimination but are restricted to optimality-based single path routing. MOSPF achieves loop-free multi-path routing, only in the restricted case of paths with identical costs. Hot potato routing achieves true multi-path routing but pays no attention to either loops or the ‘quality’ of its paths. The MPATH \[15\] algorithm and several of its variants achieve cost-sensitive loop-free multi-path routing, at the expense of routing table storage overhead proportional to the number of paths (which can be combinatorial). The theoretically best, although practically naive, solution would be all-sources, all-paths routing. This achieves the goal of correctness, however building and maintaining a complete and correct table of the entire network would be impractical for networks of any non-trivial size.

While it is still true that source and destination are the only parameters available for routing on the Internet infrastructure, there is a degree of freedom thus far unexplored by routing algorithms. Single-path deterministic routing algorithms are driven by a need to achieve loop elimination at any cost due to the disastrous effects of routing loops in such algorithms. However, for a probabilistic routing algorithm, this does not necessarily have to be the case. Therefore, if we relax the requirement for loop elimination and instead seek to achieve loop avoidance by guaranteeing to exit loops once they are entered, we are given greater flexibility in laying out optimization constraints. For this reason, we have chosen to take a probabilistic approach and to sacrifice loop elimination in favor of loop avoidance.

The undue emphasis on optimality thus far has created algorithms that aggressively eliminate loops. This has led to implementations that are intolerant of loops. On the other hand, the ability to tolerate loops opens up new exploration strategies for true cost-sensitive multi-path routing that work under the constraints presented above. We therefore begin with the terminal perspective of reachability routing, where the goal is merely to reach a destination. Hot potato routing can be viewed as a limiting example of reachability routing but we clearly want to do better. From this perspective, we are in the unique position of being able to explore the trade-off between eliminating
loops and improving efficiency of selecting paths.

Our specific formulation of reachability routing is probabilistic, multi-path, and cost-sensitive by efficiently distributing traffic among all paths leading to a destination. This type of routing can be viewed as solving an optimization problem which maximizes the number of paths between two nodes by discovering all the paths, and then derives the probability to route on a given path by assessing the path costs leading to the destination.

In particular, we study reachability routing through the lens of reinforcement learning, which provides a mathematical framework for describing and solving sequential Markov decision problems (MDPs). The states are the nodes, the actions are the choice of outgoing links, and rewards correspond to path costs associated with the state transitions. A value function imposed on the MDP (e.g., discounted sum of rewards along a path) essentially leads to an optimization problem, whose solution is a policy for routing. Intrinsically, this is what all routing algorithms based on dynamic programming do. However, single-path routing algorithms learn the best deterministic policy that solves the MDP. In this paper, the routing algorithm learns stochastic policies that achieve cost-sensitive multi-path routing.

Our previous work [13] has indicated that such an approach achieves true multi-path routing, with traffic distributed among the multiple paths in inverse proportion to their costs. In addition, in order for our reachability routing protocol to be of practical use, we are guiding our design decisions by the requirement that the protocol work within the confines imposed by the currently deployed Internet Protocol (IP) architecture.

While multi-path routing is not new, we believe that our notion of reachability routing represents a promising new direction in the field. Applying reinforcement learning in this way is a powerful tool enabling reachability routing to optimize overall network throughput, while at the same time providing built-in fault tolerance and path redundancy. Additional applications of reinforcement learning within this domain hold the potential to further optimize routing behavior by adaptively refining the performance parameters of the algorithm in response to changes in the network topology.

The remainder of this paper is organized as follows: Section II provides an overview of reinforcement learning, its applicability to network routing, and significant previous work done on the topic. In Section III we introduce a new model-based routing algorithm based on RL and describe its implementation in Section IV. Section V presents evaluation results and Section VI concludes with a summary of our contributions and directions for future research in the area.

2 Ants and Reinforcement Learning

Reinforcement learning [6] [11] is the process of an agent learning to behave optimally, over time, as a result of trial-and-error interacting within a dynamic environment. Reinforcement learning problems are organized in terms of discrete episodes, which, for the purposes of packet routing, consist of a packet finding its way from an originating source to its intended destination. Routing table probabilities are initialized to small random values, thus enabling them to begin routing immediately except that most of the routing decisions will not be optimal or even desirable. To improve the quality of the routing decision, a router can ‘try out’ different links to see if they produce good routes, a mode of operation called exploration. Information learned during exploration can
be used to drive future routing decisions. Such a mode is called *exploitation*. Both exploration and exploitation are necessary for effective routing.

Our RL routing algorithm is a form of ant-colony optimization [4], in which messages called *ants* are used to explore the network and provide reinforcements for future packet routing. The ants transiting the network provide intermediate routers with a sense of the reachability and relative cost of reaching the node which the ant originated from. In order to overcome the problems of selective path reinforcement, which deterministically converge to shortest paths, our model separates the data collection aspects of the algorithm from the packet routing functionality, as was proposed by Subramanian et al. [10]. In our model the ants only perform the role of gathering information about the network, which is then used to guide packet routing decisions.

Three parameters must be considered when applying ants in a routing framework: the rate of generation of ants, the choice of their destinations, and the routing policy used for ants. RL algorithms perform iterative stochastic approximations of an optimal solution, so the rate of ant generation directly affects their convergence properties, shown by Di Caro et al. in AntNet [3]. From a practical perspective in multi-path routing, we would like to choose destinations for the ants that will provide the most useful reinforcement updates; hence a uniform distribution policy assures good exploration. Finally, the policy used to route ants affects the paths that are selectively reinforced by the RL algorithm. As our goal is to discover all possible paths, the policy used to route ants should be independent of that of the data traffic. If we do not separate the policies, then we would end up with the same problem of selective reinforcement as found in the Q-routing [10] algorithm.

In the context of reinforcement learning using ants, effective credit assignment strategies rely on the expressiveness of the information carried by the ants. The central idea behind credit assignment is to determine the relative quality of a route and apportioning blame. In the case of routing, credit assignment creates a push-pull effect. Since the link probabilities have to sum to one, positively reinforcing a link (push) results in negative reinforcements (pull) for other links.

In the simplest form of credit assignment, called backward learning, ants carry information about the ingress router and path cost as determined by the network’s cost metrics. At the destination, this information can be used to derive reinforcement for the link along which the ant arrived [10]. Another strategy, known as forward learning, is to reinforce the link in the forward direction by sending an ant to a destination and bouncing it back to the source [3]. Subramanian et al. [10] adapt the former approach. Ants proceed from randomly chosen sources to destinations independent of the data traffic. Each ant contains the source where it was released, its intended destination, and the cost $c$ experienced thus far. Upon receiving an ant, a router updates its probability to the ant source (not the destination), along the interface by which the ant arrived. This is a form of backward learning and is a trick to minimize ant traffic.

Specifically, when an ant from source $s$ to destination $d$ arrives along interface $i_k$ to router $r$, $r$ first updates $c$ (the cost accumulated by the ant thus far) to include the cost of traveling interface $i_k$ in reverse. $r$ then updates its entry for $s$ by slightly nudging the probability up for interface $i_k$ (and correspondingly decreasing the probabilities for other interfaces). The amount of the nudge is a function of the cost $c$ accumulated by the ant. It then routes the ant to its desired destination $d$.

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In particular, the probability $p_k$ for interface $i_k$ is updated as:

$$p_k = \frac{p_k + \Delta p}{1 + \Delta p}, p_j = \frac{p_j}{1 + \Delta p},$$

$$1 \leq j \leq n, j \neq k$$

where $\Delta p = \lambda \frac{1}{f(c)}$, $\lambda > 0$ and $f(c)$ is a non-decreasing function of $c$.

Two types of ants, regular ants and uniform ants, are supported to handle the routing aspect of the algorithm. Regular ants are forwarded probabilistically according to the routing tables, which ensure that the routing tables converge deterministically to the shortest paths in the network. Regular ants treat the probabilities in the routing tables as merely an intermediate stage towards learning a deterministic routing table. They are good exploiters and are beneficial for convergence in static environments. With uniform ants, the ant forwarding probability follows a uniform distribution, wherein all links have equal probability of being chosen. This ensures a continued mode of exploration and helps keep track of dynamic environments. In such a case, the routing tables do not converge to a deterministic answer; rather, the probabilities are partitioned according to the costs. The constant state of exploration maintained by the uniform ants ensures a true multi-path forwarding capability.

### 3 Motivation

Our primary design objective is to achieve cost-sensitive multi-path forwarding, while at the same time eliminating the entry of loops as much as possible. We have made a series of improvements to the uniform ants algorithm proposed by Subramanian et al. [10], culminating in a novel model-based routing algorithm.

Let us begin by observing that uniform ants are natural multi-path routers; according to Proposition 2 in Subramanian et al. [10], the probability of choosing an interface is aligned in inverse proportion to cost ratios. The reader might be tempted to conclude that uniform ants inherently support
reachability routing; however consider the three velcro topologies of Figure 1. These topologies have the same underlying graph structure but differ in the costs associated with the main branch paths (the direct path from 0 to 19, and the path through nodes 1, 7, and 13).

Uniform ants explore all available interfaces with equal probability; while this makes them naturally suitable for multi-path routing, it also creates a tendency to reinforce paths that have the least amount of decision making. To see why, recall that the goodness of an interface is inversely proportional to a non-decreasing function of the cost of the path along that interface. The cost is not simply the cost of the shortest path along the interface, but is itself assessed by the ants during their exploration; hence the routing probability for choosing a particular interface is implicitly dependent on the number of ways in which a costly path can be encountered along the considered interface. The presence of loops along an interface means that there are greater opportunities for costly paths to be encountered (causing the interface to be reinforced negatively) or for the ants to loop back to their source (causing their absorption, and again, no positive reinforcement along the interface).

The basic problem can be summarized by saying that “interfaces that provide an inordinate number of options involving loops will not be reinforced, even if there exists high-quality loop-free sub-paths along those interfaces.” Mathematically, this is a race between the negative reinforcements due to many loops (and hence absorptions), and positive reinforcements due to one (or few) short or cheap paths. As a result, the interface with the fewer possibilities for decision making wins, irrespective of the path cost. Hence in the topologies shown in Figure 1 uniform ants will reinforce along: the costliest path (left), among one of many cheapest paths (center) and the cheapest path (right). Notice that using regular ants to prevent this incessant multiplication of probabilities is not acceptable, as we will be giving up the multi-path forwarding capability of uniform ants.

Ideally, we want our ants to have selective amnesia, behaving as uniform ants when it is important to have multipath forwarding and morphing into regular ants when we do not want loops overshadowing the existence of a cheap, loop-free path. We present a model-based approach that achieves this effect by maintaining a statistics table independent of the routing table. The basic idea is to make routers recognize that they constitute the fulcrum of a loop with respect to a larger path context.

For instance, in Figure 1 nodes 1, 7, and 13 form fulcrums of loops, which should not play a role in multi-path forwarding from, say, node 0 to node 19. The statistics table maintains, for each router (node) and destination, the number of ants generated by it and the number that returned without reaching its intended destination. Using these statistics, for instance, node 1 can reason that all ants meant for destination 19 returned to it, when sent along the interface leading to node 2. This information can be used to reduce the scope of multi-path forwarding, on a per-destination basis. The statistics table serves as a discriminant function for the choices indicated by the routing table, while the routing table reflects the reinforcement provided by the uniform ants.
4 Protocol Model

4.1 Ant Structure

Ants are small packets used to explore and gather information about the network. Periodically each source node \( s \) generates, to every other destination \( d \), ants of the form \([s, d, c, o_i]\), where \( c \) is the cost associated with the ant and \( o_i \) is the outgoing interface from the source router. When the ants are created the cost \( c \) is initialized to 0. All the intermediate routers along the path from the source to destination increment the cost \( c \) to reflect the cost in reverse (when a message traverses a link from node \( a \) to node \( b \), \( c \) is incremented by the cost of the link from \( b \) to \( a \)). When the ant reaches the destination \( d \), the cost \( c \) is the end-to-end cost of sending a message from source \( s \) to destination \( d \). Note the intermediate nodes along the path do not update \( o_i \).

4.2 Routing Table Structure

The routing table at each node is a two-dimensional array of the probabilities of using various interfaces to reach destinations. \( \text{RoutingTable}_{i}[j][k] \), maintained at node \( i \), is the probability with which the interface \( k \) of node \( i \) is chosen to reach destination \( j \). Initially the probabilities for all destinations are distributed equally across all the interfaces. This is in-line with the destructive property of RL routing algorithms in which all interfaces are “innocent until proven guilty.”

4.3 Statistics Table Structure

The statistics table is also a two dimensional structure like the routing table, except each node has two statistics tables. \( \text{SentStatTable}_{i}[j][k] \) corresponds to the number of ants sent along interface \( k \) to destination \( j \) originating from node \( i \), and \( \text{ReturnedStatTable}_{i}[j][k] \) is the number of ants sent along the interface \( k \) to destination \( j \) which returned to their source \( i \).

The ant statistics are maintained only at the source node, and not at the intermediate nodes, to allow for scalability of the algorithm. If every intermediate node \( n \) along the path of an ant from source \( i \) to destination \( j \) increments its statistics table \( \text{SentStatTable}_{n}[j][m] \) when it forwards the ant along the interface \( m \), it would necessitate the ant to have a provision to save the outgoing interface for each node along its path, so that the node will be able to identify if the ant loops back to itself. Accommodating such a structure in large topologies would result in unbounded growth of the ant’s size. Additionally, the ants are not forwarded when they reach the destination or the source. By updating the statistics table only at the source nodes, if the ant doesn’t loop back to itself, the source node can safely assume that it has reached the destination (Under 100% reliability conditions that no packets are dropped); whereas the intermediate nodes would have no way of determining whether the ant reached the destination successfully, or whether it looped back to the source node itself.
Table 1: Model-based Ant Routing Algorithm

procedure Main
begin:
    Uncontrolled Exploration
    Controlled Exploration
end.

procedure Exploration (Uncontrolled | Controlled)
begin:
    for every node in the topology
    begin:
        GenerateAnt; /* Periodically Generate Ant */
        SelectInterface (Uncontrolled | Controlled);
        UpdateModel;
        ForwardAnt;
    end.
end. /* End of exploration procedure */

procedure ReceiveAnt
begin:
    if the receiving node is the source of the ant
    begin:
        UpdateModel;
        DestroyAnt;
    end.
    if the receiving node is
    neither the source nor the destination
    begin:
        UpdateRouteTable;
        SelectInterface(Uncontrolled | Controlled)
        ForwardAnt;
    end.
    if the receiving node is the
    intended destination of the ant
    begin:
        UpdateRouteTable;
        DestroyAnt;
    end.
end. /* End of receive ant procedure */
4.4 Description of the Algorithm

An overview of the algorithm is given in Table 1. The algorithm consists of two stages: Uncontrolled Exploration and Controlled Exploration. In both forms of exploration, each node periodically generates ants destined for every other node in the topology. The algorithm uses uncontrolled exploration to collect information about the topology and uses that information to build a model to control future exploration at the nodes. The information collected during the controlled exploration is used to update the model as well. The two forms of exploration work almost identically except for the SelectInterface method. The following is a brief description of the various methods used in the algorithm above.

4.4.1 GenerateAnt

This method generates an ant of the form \([s, d, 0, \text{undefined}]\), where \(s\) is the source node generating the ant and \(d\) is the intended destination. The initial cost \(c\) associated with the ant is set to 0. The SelectInterface method determines the output interface, so at this point, the output interface is undefined immediately after the ant is created.

4.4.2 SelectInterface

Due to the probabilistic nature of the routing algorithm, it is essential to ensure that the choice of the destination node for each ant at each node is uniformly distributed, so that the number of ants generated to the various destinations is nearly equal. This method differentiates between the two forms of exploration mentioned above, however both forms choose the output interface uniformly, although the valid interfaces for Controlled Exploration are slightly constrained for optimization.

- **Uncontrolled Exploration:** Here the choice of the outgoing interface at each node along the path from the source to destination is unbiased, i.e. every interface at that node has equal probability of being chosen as the outgoing interface. The node generating the ant chooses one interface from its interfaces and forwards the ant along that interface. If an intermediate node (not the intended destination node) receives an ant along interface \(A\) and has interfaces other than \(A\), it forwards the ant on some interface other than \(A\). If it does not have any other interface then it sends-back along the interface \(A\) itself.

- **Controlled Exploration:** Here the choice of outgoing interface is controlled by a variable called the threshold factor \((\tau)\) ranging from 0 to 1. The threshold factor not only affects the multipath capabilities of the routing algorithm, but also its loop-free capabilities and its correctness with respect to the routing of packets (measured by the percentage of packets successfully reaching their intended destinations).

Formally, the threshold factor works in the following manner: When a node \(i\) (source or intermediate) needs to forward an ant intended for destination \(j\), finds the ratio of \(\text{ReturnedStatTable}_i[j][k]\) to \(\text{SentStatTable}_i[j][k]\) for each of its interfaces \(k_1 \cdots k_n\). All those interfaces whose ratios are less than the threshold \(\tau\) are eligible for selection as a forwarding interface. Then the selection policy is
to choose among the eligible interfaces with equal probability. Three special cases must be handled in the case of controlled exploration:

- **Case 1** When an ant arrives at a leaf node, i.e. there are no other interfaces other than the incoming interface, and if it is not the intended destination then the node sends-back the ant along the same interface.

- **Case 2** When all the interfaces at the intermediate node are ineligible, i.e. their statistic table ratios are above the threshold, then the node sends-back the ant along the interface it originally received the ant from.

- **Case 3** When all the interfaces at the source node are ineligible then the source node uses the uncontrolled exploration selection policy to break the deadlock. This case is a very rare occurrence and occurs only when is set to a very low value.

Once the outgoing interface is selected the next step is to forward the ant along the chosen interface (ForwardAnt). In the case of source node, before calling the ForwardAnt, UpdateModel is called to update the statistics table.

### 4.4.3 UpdateModel

This method updates the statistics tables when an ant is generated or loops back to its source. The correctness and currency of the statistics tables are vital to the performance of the router. When the node generates the ant \([i, j, c, k]\), it increments its statistic table entry \(\text{SentStatTable}_{i}[j][k]\) by 1 to indicate that interface \(k\) was chosen by \(i\) to forward the ant intended for destination \(j\). Also, when an ant \([i, j, c, k]\) loops back to the source node, the statistic table entry \(\text{ReturnedStatTable}_{i}[j][k]\) is incremented by 1 to indicate that the choice of interface \(k\) to route the ant intended to destination \(j\) resulted in a loop. This can be considered a negative reinforcement in the behavior of the router.

### 4.4.4 ForwardAnt

This method is used to forward the ants from the current node to the next node along the interface chosen by the SelectInterface method.

### 4.4.5 DestroyAnt

When the ant reaches the intended destination or loops back to its source itself, the ant is not forwarded further and the node absorbs the ant.

### 4.4.6 UpdateRouteTable

When any node \(t\) (intermediate or the intended destination) other than the source node, receives an ant \([i, j, c, k]\) on interface \(l\) from node \(y\), it updates the cost \(c\) by adding the cost of traversing
the interface $l$ in reverse, and then updates its routing table entries for node $i$ as follows:

$$rt[i][l] = \frac{rt[i][l] + \Delta p}{1 + \Delta p}, rt[i][m] = \frac{rt[i][m]}{1 + \Delta p}$$

where $1 \leq m \leq n, l \neq m$

where $\Delta p = \frac{1}{f(c)}, \lambda > 0$ and $f(c)$ is a non-decreasing function of $c$.

4.5 Qualitative Characteristics

The model-based routing algorithm presented above discards all useless loops, in which all traffic exiting the loop must exit at the same point which it entered, such as the fulcrum points in the velcro topologies shown in Figure 1. For instance, in these velcro topologies, when node 1 sends out a packet intended for a destination other than those nodes in the loop pivoted at 1, either on the interface leading to node 2 or node 6, the result will be the packet returning to node 1. From the statistics table, node 1 will learn that those interfaces are useless for forwarding packets to certain destinations and hence avoid them in the future. By discarding all the useless loops, this algorithm overcomes the problem of the uniform ants algorithm wherein only the path with the least decision-making is reinforced.

The threshold factor $\tau$ influences the reinforcement of the various paths of a topology. At very high values of $\tau$, the algorithm tends towards behaving like uniform ants while continuing to avoid all the useless loops. For instance a $\tau$ value of 1 means that an interface where all but one packet sent on it looped back may still be selected as an outgoing interface. At the same time this setting still avoids all the interfaces that lead to useless loops, as all packets sent along them must have come back to the sender.

At high $\tau$ values, certain packets may encounter one or more loops along their path that are unavoidable. At very low values of $\tau$, the nodes have a limited selection of interfaces to choose from due to the stringent loop-avoidance criteria, which will affect our goal of multi-path routing, but will greatly decrease the probability of encountering a loop. The choice of $\tau$ factor determines the multipath, correctness, and loop-avoidance capabilities of our algorithm. The threshold factor can either be set to a fixed value (for the network, or on a per-router or per-router/destination-pair basis) or can be adaptively refined to optimize model-based routing for various criteria.

5 Evaluation

5.1 Experimental Setup

To measure the performance of our cost-sensitive reachability routing algorithm, we wrote a discrete event simulator in C to simulate a standard point-to-point topology based network. The simulated network is modeled as a set of nodes interconnected over point-to-point links, each with an associated cost. The discrete event simulator was derived from work done in [14], and has been used in several networking courses to model routing algorithms.
The simulator runs at a resolution of 1 µs and an integer value defined at the initialization of the simulation determines the duration of the simulation. In our case, the simulation runs were set to INTMAX (2147483647 as defined in <limits.h>). As it is a discrete event simulator, every action takes place after the expiration of a timer and the simulator is programmed to run in uncontrolled exploration mode for the first one eighth of the time and in controlled exploration mode for the remaining time. Each node generated an ant every 10000 µs. For the purpose of this paper, we programmed the link layer of the simulator to be reliable, i.e. it does not introduce any errors or drop packets.

5.2 Topologies

A utility provided along with the simulator [14], when given the number of nodes in the network and number of interfaces per node, is able to generate four different interconnected topologies for the network, namely: tree, clique (fully connected mesh), arbitrary graph, and loop topologies. The automated topology generating utility was used to generate the tree and arbitrary graph topologies used in the simulations.

Using the manual topology generator provided along with the simulator, complex topologies such as the velcro and dumbbell topologies were created. These topologies have some intrinsic characteristics helpful in demonstrating the range and effectiveness of our algorithm.

A clique topology generator was written in C, which, when given the number of rows and columns in the clique, will generate a perfect clique topology wherein all the interior nodes will be of degree 4 and all the boundary nodes will be of degree 2 or 3.

Finally, BRITE, the Boston university Representative Internet Topology gEnerator [7], was used to generate large Internet scale topologies. It provides a wide variety of generation models, as well as the ability to extend such a set by combining existing models or adding new ones. We used the Router Waxman Flat Router-level model, which is governed by a power law, to generate the topologies. A program in C was written to convert the topology format generated by BRITE to the format used by our simulator. Topologies with sizes ranging from 20 to 200 nodes were generated using BRITE.

Our model-based routing algorithm was first validated in [13], by examining its performance when applied to routing on synthetic worst-case scenario topologies, such as velcro topologies. This previous work also presented a subtle modification to the algorithm, avoiding sub path reinforcement, which results in better performance on certain types of topologies.

The primary contribution of this work is to study data traffic across the network based on converged routing tables and introduce a new factor called the reachability factor (φ) that controls the choice of the outgoing interfaces. We investigate the effect of the threshold factor (τ) and the reachability factor on various topologies with the help of an operating curve aimed at helping network administrators in choosing the ideal threshold and reachability factors for their networks. We also show that by making the nodes always choose the interface with the highest probability for the intended destination, our model-based routing algorithm behaves in the same way as any other single-path deterministic routing algorithm i.e., it provides loop-free shortest-paths with guaranteed delivery for all packets.
Additionally, we show that even though the goal of every multi-path routing algorithm is to avoid loops, our model-based routing algorithm does not guarantee a complete elimination of loops. Nevertheless, our algorithm guarantees that a packet will eventually exit the loop and reach its intended destination. We study the distribution of loops encountered by packets and show that a vast majority of packets encounter only a small number of loops, or none at all.

5.3 Packet Routing Using Model Based Routing

In this set of experiments, a new application was written on top of the simulator to route packets based on the routing table learned by ants exploring the network. Initially, we ran the model-based routing algorithm on the given topology to obtain a stabilized routing table. Next, we ran the application with the routing table and the reachability factor as parameters and collected various statistics. Below we will discuss in detail the application, the reachability factor, the statistics collected, and analysis of the statistics obtained from both model-based and uniform ants routing.

The functioning of the application is similar to the one described earlier, except that there is no update of the routing table. The routing table is pre-initialized to that obtained from the model-based routing simulation and remains constant throughout. By not updating the routing table based on the packets arriving at every node we are just exploiting the model and not exploring the network further. It should be noted that a real world router would constantly explore the network with ants, and use the resulting routing table to route packets simultaneously. However, to determine the effectiveness of the underlying algorithm, it is simpler to analyze its performance in a static network environment.

The reachability factor $\phi$ controls the degree of freedom each node has in choosing the outgoing interface. At each node the outgoing interfaces are ordered in descending order of their probabilities for every destination. When a node $n$ needs to route a packet intended for destination $d$, it picks the top $\phi$ interfaces for that destination and uses their scaled up probabilities for selecting the outgoing interface. For a better understanding of the reachability factor, consider the following example. Say a node $M$ has 4 interfaces $A$, $B$, $C$, and $D$ with associated probabilities $0.4$, $0.2$, $0.15$, $0.15$ for destination $N$; then a $\phi$ value of 2 will allow the node $M$ to choose from interfaces $A$ and $B$ with probabilities $(0.4)/(0.4 + 0.2)$ and $(0.2)/(0.4 + 0.2)$ respectively i.e. node $M$ will choose interface $A$ $66.67\%$ of the time and interface $B$ $33.33\%$ of the time to route the packet intended for destination $N$.

The statistics collected include the number of loops encountered by the packets along their paths, the number of packets encountering loops, the multipath capability of the packets, and the percentage of packets successfully reaching their intended destination. To determine the number of loops encountered by the packets, each packet has a stack associated with it. Every node, before forwarding a packet, checks to see if its id already exists in the stack. If its id is present in the stack, it increments the loop counter of the packet by 1 and pops the contents of the stack up to its id else pushes its id onto the stack and then forwards the packet. At the end of the simulation we have statistics on the number of packets encountering loops (loop percentage) and the total number of loops encountered by all the packets. Every packet also has a multipath flag associated with it that is set if any node along the path taken by the packet has more than one outgoing interface to choose from. This is used to determine the percentage of packets that could have potentially
taken more than one path to reach their intended destination (multipath percentage). Finally, we determine the success percentage as the percentage of packets successfully reaching their intended destination.

5.3.1 Reachability factor $\phi = 1$

In our first set of experiments $\phi$ was set to 1 so that the nodes always choose the best outgoing interface (interface with the highest probability) for each packet. As each packet deterministically chooses the best interface at every node, the multipath percentage is zero. A $\phi$ value of 1 also results in the avoidance of loops and a one hundred percent success percentage as all the packets reach their intended destination. According to proposition 2 of Subramanian et al. [10] the probability of choosing an interface is inversely proportional to the cost ratios (under the assumption of loop free paths). Keep in mind that this proposition applies even for our modified model-based algorithm as all the avoidable loops are avoided and also we have shown in [13] that the probabilities are inversely proportional to the path costs. By choosing the interface with the highest probability, i.e. the interface that advertised a lower cost path to that destination, at every node we have achieved deterministic shortest path routing while still using the underlying probabilistic routing table.

The following set of simulations were done on 20 to 100 node BRITE topologies with uniform cost distribution so that with $\phi = 1$ the path taken by all the packets will not only correspond to the shortest path in terms of cost but also in terms of the number of hops. By sending packets across the network and keeping track of their hop count, we ascertained the shortest path length between every source-destination pair. At the end of the simulations, the average shortest path length for the topologies were calculated and compared with the theoretical shortest path lengths. We then attempt to fit this empirical data onto parametrized formulas.

Below we discuss the derivation of average shortest-path lengths for exponentially distributed graphs based on [8]. The Router Waxman model of BRITE uses an exponentially distributed generation function to create the topologies. According to [8], the generating function $G_0(x)$ should be normalized such that $G_0(1) = 1$.

We use the following generating function for our derivation:

$$G_0(x) = \frac{1 - e^{-1/\kappa}}{1 - xe^{-1/\kappa}}$$

According to [8], the average shortest path length is given by:

$$l = \frac{\ln N/z_1}{\ln z_2/z_1} + 1$$

for $N \gg z_1$ and $z_2 \gg z_1$, where $N$ corresponds to the number of nodes in the topology, and $z_m$ corresponds to the average number of $m$th-nearest neighbors with $z_1 = G'_0(1)$ and $z_2 = G''_0(1)$. We derived $l$ to be:

$$l = 1 + \frac{\ln N + \ln e^{1/\kappa} - 1}{\ln 2 - \ln e^{1/\kappa} - 1}$$
From this equation we derived the value of $\kappa$ to be

$$\kappa = \frac{1}{\ln \frac{N^t}{N^s}}$$

Based on the above derivations, a least square fit was conducted on the simulation results, which returns both $\kappa$ and the square of the correlation coefficient with values ranging of 0 and 1, indicating bad or good fit respectively. In our case, the fit returned a value of 0.986551, which indicates that the best fit line summarizes the data very well as shown in Figure 2.

5.3.2 Reachability factor $\phi = \text{maximum degree}$

By setting the reachability factor to the maximum degree of the topology, each node will be allowed to choose among all its interfaces to be the outgoing interfaces (based on the probability associated with it for the intended destination). The simulations were run on the following topologies: 20 to 200 node BRITÉ topologies, 10x4 & 8x5 clique topologies and the velcro topologies described in Figure 1. Operating curves of the percentage of packets encountering loops were plotted against the percentage of those with multipath capabilities for various topologies at different values of the threshold factor. These operating curves are shown in Figures 3, 4, and 5. Visualizing the performance of the routing algorithm in this way enables us to compare the effect of the inherent topology and performance parameter settings, and the interactions between the two.

As opposed to $\phi = 1$, $\phi = \text{maximum degree}$ results in multi-path forwarding of the packets and also some portion of packets entering into loops. All the packets reached their intended destinations except for those that looped back to their source resulting in a high success percentage. To overcome the drop in success percentage, the packets were forwarded even when they looped back to the source and counting this episode as just another loop encountered along the path.
With this modification all the packets successfully reached their intended destinations but with a linear increase in the percentage of loops (to account for all those packets that were earlier absorbed by their source). All packets had a TTL of 255 but none of them were dropped due to reaching the TTL limit. Below we present the operating curves for various topologies under both the cases: 1) absorption of packets at their source and 2) no absorption of packets.

### 5.4 Operating Curve Observations

Let us take the operating curve for a random 40 node BRITE topology shown in Figure 3(a) and study it closely. As the threshold factor increases, we see that the performance goes from a region with no loops and 45% multipath to one with 7% loops and 100% multipath. It is heartening to note that the curve first increases in the direction of accommodating multipath before introducing loops, rather than the other way around.

Second, notice that different portions of the graph are shaded differently. Each operating curve is represented by a solid line and a dotted line. These denote the region where the model is completely in force, and the region where it is not, respectively. As discussed earlier, at very low threshold factor values, when all the interfaces at an intermediate node are ineligible, i.e. their statistic table ratios are above the threshold, then the node sends-back the ant along the interface it originally received the ant from resulting in an increased percentage of packets entering into loops. Similarly at very low values of $\tau$, when all the interfaces at the source node are ineligible, then the source node uses the uncontrolled exploration selection policy to break the deadlock. As Figure 3(a) shows, around a threshold value of 0.4, the model comes into force in that all routing decisions are based on learning rather than defaults.
(a) With source absorption, each point is labeled with its threshold value and success percentage
(b) Without source absorption, each point is labeled with its threshold value

Figure 4: Operating curve for the velcro topology shown in Figure 1 right

(a) With source absorption, each point is labeled with its threshold value and success percentage
(b) Without source absorption, each point is labeled with its threshold value

Figure 5: Operating curve for a 8x5 clique topology
By comparing Figure 3(a) with 3(b) (the latter of which does not have source absorption), we notice that the difference in the percentage of success of packets reaching their destination with and without source absorption is reflected in the difference in percentage of packets encountering loops with and without source absorption. Removing source absorption from the simulation results in a 100% success rate, but an increase in the percentage of packets encountering loops, which is an understandable consequence. However, for a router using the ant-derived statistic tables to make routing decisions, it is vital for data to transit the network with the highest success rate, even at the expense of an increased likelihood of entering a routing loop.

The operating curves for the 40 node BRITE topologies shown in Figures 3(a) and 3(b), compared to the operating curves of BRITE topologies with different numbers of nodes (not shown here, refer to [12]) also exhibit another interesting behavior. As the number of nodes in the topology increases, the minimum multipath percentage also increases. This is due to the fact that at very low threshold values, the model-based routing algorithm routes a large number of packets deterministically in smaller topologies. The shape of the operating curve greatly depends on the intrinsic graph theoretic property of the topologies. The reader can observe from the figures above that each topology class (BRITE, clique, and velcro) generates its own unique shape of operating curve.

The reader should also observe that all the operating curves at $\tau = 1$ exhibit the behavior of the uniform ants algorithm [10]. This is due to the fact that all the interfaces at each node are eligible to be selected as the outgoing interface for the intended destination which conforms to the selection policy of uniform ants algorithm.

The number of unique operating curves is limitless when the various topology classes are combined in the same network. The fact that each operating curve has a unique threshold value that gives the network optimal performance, in terms of loop avoidance and multipath routing, presents us with the need to adaptively learn and refine that threshold value for an arbitrary dynamic network. This is an area of future research that is necessary before our multipath routing algorithm can be deployed on actual networks.

5.5 Distribution of loop frequency

Finally, we show that even though the presence of loops is unavoidable, the number of packets that encountered $k$ loops along their paths to their respective destinations exponentially decays with increase in $k$, i.e. the majority of the packets encounter between 0 to 2 loops, suggesting a power law. Figure 6 shows the plot between loop distribution and packet frequency for a 40-node BRITE topology. It should be noted that due to the cyclic nature of clique topologies, certain packets in those topologies encounter as many as 20 loops before they reach their intended destination.

5.6 Verification of cost-sensitive routing in BRITE topologies

The goal of this experiment was to perform a large-scale validation of the cost-sensitivity properties of our reachability routing algorithm. First, all the paths taken by various packets at $\phi = \text{maximum degree}$ were enumerated. To achieve this, every packet had a stack associated with it that kept track of the nodes visited by it en route to its destination. At the destination, the paths taken by the packets from each source were ranked in increasing order of their costs. The destination nodes only
kept track of unique paths from each source and also maintained the frequency associated with each path.

The purpose of this instrumentation was to ensure that the frequency of costs, as measured through pursued paths, mirrored the distribution of traffic along these paths. At the end of the simulation, the summation of frequency over the top \([x-9\%, x\%]\) of the paths for every source-destination pair was determined, for \(x \in [10, 20 \cdots 100]\). Figures 7(a) and 7(b) show the cost-sensitive routing of our model-based algorithm and also that sub-path reinforcement has no effect on BRITE topologies. (The experiments were performed on 60-node BRITE topologies).

6 Conclusion and Future Work

In this paper we have presented a new model-based reinforcement learning algorithm, which achieves true cost-sensitive reachability routing, even in network topologies that pose problems to both deterministic routing as well as classical RL formulations. This algorithm efficiently distributes traffic among all paths leading to a destination. The evaluation results indicate that our approach achieves true multi-path routing, with traffic distributed among the multiple paths in inverse proportion to their costs. By helping maintain the incremental spirit of current backbone routing algorithms, this approach has the potential to form the basis of the next generation of routing protocols, enabling a fluid and robust backbone routing framework. The reader is referred to [12] and [13] for background and further experimental results.

We now present four possible directions for future work.

- **Adaptive configuration of the threshold factor (\(\tau\))**
  
The threshold factor is currently set to a fixed value for all the nodes in the topology. From the operating curve, the network administrator determines the optimal value of \(\tau\) at which
the routing yields high success and multipath percentage while keeping the percentage of packets entering into loops low. As part of the future work, we can determine the $\tau$ value dynamically based on available information and periodically adjust its value to obtain the optimal routing requirements. The value could be dynamically adapted on a per-node basis or on per-source/destination-pair basis at every node.

- **Instructive feedback**
  
  Our RL algorithm works primarily using evaluative feedback from neighboring routers. It would be interesting to extend the framework to accommodate instructive feedback. But to provide instructive feedback, a router must have sufficient discriminating capability to perform credit assignment. It is typically of the case that any resulting instruction will be of the negative kind i.e., “for destination $X$, do not use interface $i_y$.” How such negative instructions can co-exist with positive reinforcements is an important research issue, not only for our application domain, but also the larger field of reinforcement learning.

- **Modeling topologies with hierarchical addressing**
  
  Currently the algorithm assumes all topologies to be flat such that all nodes in the topology are numbered from 1 to $n$. By supporting hierarchical addressing of the nodes, the model built at every node could be at a sub network basis instead of being at a per node basis, i.e. a node could collect statistics for a group of nodes as a single entity and build its model accordingly. Such an approach encourages problem decomposition and enables scaling up to large network sizes.

- **Reverse engineering routing protocols**

Figure 7: Traffic distribution in a random 60 node BRITE topology without source absorption, note the logarithmic scale of the y-axis.
The model-based reinforcement learning algorithm presented here promises to serve as an abstraction of reachability routing algorithms in general. One idea for further research is to automatically mine the model by analyzing implemented routing algorithms’ behavior, rather than incrementally learning it from scratch, as we have done here. In other words, we can seek to imitate the functioning of another algorithm by suitably configuring our model. This problem has its roots in inverse reinforcement learning, where we are aiming to recover an algorithm from observed (optimal) behavior. The first steps toward such reverse engineering have been recently taken [9].

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