Game Theoretic Stochastic Routing for Fault Tolerance on Computer Networks

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Abstract

Most of today's Internet routing protocols forward packets of a connection over a single path. This means that, even if redundant resources are available, a single failure (accidental or due to malicious activities) along a route will interrupt connections that use that route. Given the reactive approach to failure recovery that most current routing protocols employ, these communication disruptions may last for long enough time to be noticeable by higher protocol layers. Also, given that the path over which a connection's packets travels is fairly predictable and easy to determine, connections are vulnerable to *packet interception* and *eavesdropping* attacks. In this paper, we introduce the Game-Theoretic Stochastic Routing (GTSR) framework, a proactive alternative to today's reactive approaches to route repair. GTSR minimizes the impact of link and router failure by: (1) computing multiple paths between source and destination and (2) selecting among these paths randomly to forward packets. Moreover, besides improving fault-tolerance, the fact that GTSR makes packets take random paths from source to destination also improves security. For example, it makes connection eavesdropping attacks maximally difficult as the attacker would have to listen on all possible routes.

The approaches developed are suitable for network layer routing as well as for application layer overlay routing and multi-path transport protocols such as SCTP. Through simulations, we validate our theoretical results and show how the resulting routing algorithms perform in terms of the security/fault tolerance/delay/throughput trade-off. We also show that a beneficial side-effect of these algorithms is an increase in throughput, as they make use of multiple paths.

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I. INTRODUCTION

"Traditional" routing protocols forward packets belonging to a connection over a single path from source to destination. For instance in the network shown in Figure 1, although there are multiple paths between the two nodes marked as source (s) and destination (d), single-path routing using shortest route (in terms of number of hops) will forward a connection's packets over the lower (darkened) path. This means that, even if redundant resources are available, a

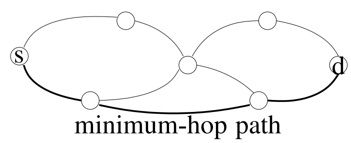


Fig. 1. Shortest-Path Routing

single failure (accidental or due to malicious activities) will temporarily interrupt all connections that use the compromised route. Eventually, this will be corrected but it can take non-negligible time, depending on how often routers ping/poll one another and how frequently routing updates are distributed. Another undesirable aspect of single-path routing is that packet interception or eavesdropping can be achieved with a minimum amount of resources, because the path over which packets travel is predictable. For example, by tapping into one of the links along a path, an attacker can reconstruct an unencrypted file transfer from eavesdropped packets, and by breaking into one router, a man-in-the-middle attack can be launched on encrypted transfers that utilize key exchange [1].

In this paper, we describe *game-theoretic stochastic routing*, or *GTSR*, which can be viewed as a proactive alternative to today's reactive approaches to route repair. GTSR explores the existence of multiple paths between network nodes and route packets to minimize predictability. It discovers all paths between a source-destination pair and determines next-hop probabilities, i.e., the probability with which a packet takes a particular next-hop along one of the possible paths. This contrasts with single path algorithms that simply determine the next-hop (i.e., the next-hop probabilities are restricted to be either one or zero). The net effect of GTSR is that packets traverse random paths, but in an optimal way. We should point out that, unlike security and fault tolerance mechanisms that are based on detection and response, GTSR takes a *proactive* approach to making connections less vulnerable to failures or attacks.

Throughout this paper we use *nodes* to refer to the network elements that forward packets. Such nodes could be network layer routers; end systems (or hosts) that participate in application layer routing (e.g., in an overlay network such as RON [2]); or act as transport layer end-points (e.g., in SCTP [3] which supports splitting of data streams over multiple paths). From this perspective, GTSR can operate at any layer of the protocol stack. In the remainder of this section, we put GTSR in perspective by reviewing some existing approaches to failure prevention and recovery.

Failures, Interception, and Eavesdropping

The Internet is particularly vulnerable to failures and attacks because data packets travel along a physical infrastructure that (i) is easily probed and (ii) is composed of thousands of elements (physical links, switches, routers, hosts, etc.) each one of them vulnerable to attacks and failures. Dynamic routing protocols are designed to try to circumvent failures in network nodes and links. However, these protocols are purely reactive and wait for failures to be detected before taking corrective measures. While some failures can be easily discovered (e.g., if there is no carrier signal, the physical layer interface will report an error) others cannot. Intermittent failures are especially difficult to detect and routing often takes considerable time to recover from them. Once link/node failures are successfully detected, alternate routes must be found. While some link-state algorithms can find alternate paths relatively quickly, distance vector algorithms may require considerably more time (often on the order of several seconds in large, poorly connected networks). In either case, during detection of the cut/failure and search for a new route, the connection is cut.

Selective faults/attacks are especially challenging. Suppose, for example, that a node of the network is compromised and that it selectively intercepts packets from specific end-to-end connections. If routing hello packets are not intercepted, other nodes do not compute new routes to exclude the compromised node. This means that application or transport layer retransmissions will keep following the same route and will continue to be subject to interception. A more "active" form of attack exploiting compromised nodes is to have them generate spurious routing updates reporting very low costs to all or some destinations. As a result, other nodes will funneled packets to these compromised nodes.

Privacy and integrity techniques (e.g., end-to-end encryption, VPNs, and secure tunnels) are effective in protecting against eavesdropping and some forms of interception (e.g., selective interception). However, if an encryption key is stolen or when defending against attackers with inside information, these techniques lose much of their effectiveness. Furthermore, man-in-the-middle attacks may still be possible. To protect a data transmission network against a wide range of attacks, one needs a suite of mechanisms spanning several layers of the protocol stack. In particular, end-to-end security mechanisms (e.g., end-to-end encryption for privacy and message authentication for integrity/authenticity) should be complemented by security mechanisms at other layers (e.g., link-layer encryption). GTSR is one such mechanism and complements security measures taken at other layers. For example, if a session key is exchanged over several packets, then GTSR makes man-in-the-middle attacks maximally difficult. Hence, GTSR coupled with encryption results in higher security than either approach could offer alone.

Exploring Multiple Paths

(Deterministic) flooding — i.e., sending each packet along every possible path — is the simplest form of multi-path routing. Applications can then rely on a reliable transport protocol to “filter-out” duplicate packets. Flooding provides a routing mechanism that is extremely robust with respect to link/node failures. However, this type of routing is not practical in most networks because it greatly increases overhead and results in (unnecessary) network resource consumption. Moreover, flooding significantly simplifies packet eavesdropping by an attacker. In fact, in order to minimize the risk of eavesdropping, no more than one packet should be sent from source to destination and the path traveled by this packet should be as unpredictable as possible.

We propose is to explore multiple paths through *statistical flooding*. In statistical flooding, packets are sent through all available paths but generally no packet is sent more than once (although error control at the transport layer may require a packet to be re-sent). Flooding thus occurs “on-average” and is randomized to minimize predictability.

Stochastic routing is the mechanism used to achieve statistical flooding. In this type of routing, nodes select the next hop where to forward a packet in a random fashion. The next-hop probabilities — i.e., the probabilities of selecting particular next-hop destinations — are design parameters and determining these probabilities is the subject of this paper. Our main challenges is determining of next-hop probabilities that ensure:

1) *Delivery*, i.e., all packets will reach their desired destination with probability one.

2) *Timeliness*, i.e., the delay is acceptable.
3) *Statistical flooding* is achieved, i.e., all paths are explored by the packet ensemble (but not by each individual packet).

With respect to 3, one should add that some nodes/links in the network may be more susceptible to failures/attacks than others and therefore it may be desirable to have non-uniform statistical flooding. For example, one may want to use stochastic routing in conjunction with intrusion detection so that, as a detector suspects that a link/node is compromised, the next-hop probabilities can be adjusted to avoid that node/link. As more data is collected and the detector gains confidence, the next-hop probabilities can reflect this more decisive knowledge. This scenario is appealing because the detectors do not need to initially make boolean decision as to whether an attack/failure has occurred or not. Thus the fundamental trade-off between false alarm rate and detection speed does not apply (cf., [4] for a discussion of such trade-offs).

Scope

One question to ask is "where can the GTSR methodology be effectively applied in today's networks?" Clearly, GTSR will only be effective if there are multiple paths to explore. At the network layer, we see at least two domains in which this technique may prove useful:

1) Inside Internet service providers (ISPs) where there are often multiple independent paths to the exit point for that ISP. GTSR would be part of the suite of tools that the ISP utilizes to provide secure networking to its clients.
2) Inside an organization that builds multi-path redundancy in its network to improve security (and also to augment throughput). An organization may utilize multiple connections to a single ISP, or even connect to multiple ISPs to connect to the outside network and employ GTSR to spread data across independent paths provided by distinct ISPs.

At application layer overlay networks, the applicability of GTSR depends on the degree to which links in the overlay network are truly independent (i.e., do not share any physical links/nodes). While the presence of dependent paths does not affect the applicability of GTSR, if there are no independent paths at the network layer, then GTSR will not increase security/reliability. On the other hand, if attacks do not target packet transmission, but application layer routers (i.e., if the risk is that end-hosts taking part in the forwarding may be compromised), then GTSR can increase reliability and security as long as the overlay network has multiple distinct paths between the source and destination.

At the transport layer, protocols such as SCTP allow data streams to be split over several paths. Again, the utility of splitting the flow depends on whether the different physical paths are distinct. Or more specifically, if the portions of the paths that are at risk of being attacked are distinct. For example, if the first hop is secure/highly reliable, but the other hops are not, and if only the first hop is common to all paths, then GTSR will provide improved reliability and security. In this case, GTSR offers an approach to split the flow in an optimal way.

Outline

The remainder of this paper is organized as follows. In the next section, we review related work. Section III develops techniques for designing optimal stochastic routing policies. Simulations of these stochastic routing policies are presented in Section IV. Finally, Section V provides concluding remarks and points towards future research. Detailed derivations of the results in Section IV are included in the Appendix.

II. Related Work

Virtual Private Networks (VPNs) [5] have been used as a way to securely interconnect a (typically small) number of sites. While private networks use dedicated lines, VPNs try to implement private networks atop a publicly-accessible communication infrastructure like the Internet. VPNs typically employ some combination of encryption, authentication, and access control techniques to allow participating sites to communicate securely.

The emergence of IPsec [6] as a IETF standardized protocol has prompted VPN solutions to use IPsec as the underlying network-layer protocol. As in any encryption-based mechanism, one drawback of IPsec is that secret keys must remain secret. As previously discussed, if an attacker is able to infiltrate a node or has “inside” information, shared and/or private keys may be compromised and the corresponding communication channels become insecure.

Onion routing [7] is another approach to security that focuses on hiding the identities of the communicators. It uses several layers of encryption, where each layer is used to encrypt the transmission between routers on each end of a link. Because of the many layers of encryption, routers are unable to decrypt the data or even the source and destination addresses. All that a router can decipher is the next-hop information. While onion routing is very effective for anonymity, it is not very efficient: each connection must be built and torn down, routers must encode and decode packets, and memory-intensive source routing is used.

Secure BGP (S-BGP) [8] makes use of public key and authorization infrastructure, as well as IPsec to verify the authenticity and authorization of control traffic generated by the Border Gateway Protocol (BGP).

Another related effort is the Resilient Overlay Networks (RON) project [2] whose goal is to improve the performance and robustness of network-layer routing. RON nodes monitor current routing paths and decide whether to choose other routes (by selecting alternate application-layer paths through other RON nodes) in order to meet application-specific performance requirements. GTSR could be implemented in such networks to improve security and fault tolerance.

The approach developed here is, in some ways, similar to that presented in [9], where members of a group cooperate to maintain their anonymity to the server. Specifically, users send their request not directly to the server but to random users in the group. Each user can then either forward the request to the server or to another member of the group. In GTSR, randomization is applied at the network layer with the goal to protect the data packet not from the destination, but from intermediate attackers.

Equal-Cost Multi-Path (ECMP) [10] and OSPF Optimized Multi-Path (OSPF-OMP) [11] are, in a way, multi-path routing algorithms. While these methods insist that the alternative paths be of equal cost, MPLS allows different paths, besides shortest paths, to be utilized. However, all of these methods are not stochastic; rather, routers employ techniques to ensure that a connection will utilize a single path[1]. Hence a link failure will result in cut connections and eavesdropping at a single link will expose connections going through that link. Furthermore, these algorithms were developed to increase throughput but not to make routing robust to attacks or failures. Hence, there is no mechanism in place to avoid links that may have been compromised or have been subject to high failure rates. In short, these, as well as other load balancing techniques, seek to optimize performance metrics such as bit-rate and delay, while in GTSR we optimize fault tolerance and security.

[1]One reason that a connection is restricted to a single path is that many of today's implementations of TCP do not work well under persistent packet reordering. However, as is discussed in Section IV, advancements in TCP have relieved this limitation.

A subset of the results in this paper were presented at the 11th IEEE Int. Conf. on Comput. Communications and Networks [12].

III. Routing Games

Within each deterministic router, there exists a routing table that associates each possible destination IP address with the address and physical interface of a next-hop router. The goal is to, at every hop, get "one-step closer" to the destination or, in case the final destination is in the local subnet, the address and physical interface of the host. Stochastic routing utilizes a distinct concept called *next-hop probabilities*, which map each possible destination IP with a probability distribution of the next-hop. Packets are forwarded by selecting the next-hop at random, but according to the next-hop probability distribution. From an end-to-end perspective, this results in data packets following random paths. The main challenges in stochastic routing is the determination of next-hop probabilities that ensure: *delivery*, *timeliness*, and *statistical flooding*. The key technical insight explored here is to formalize the stochastic routing problem as an abstract game between two players: the designer of the routing algorithm, which is represented by *routers*, and an *attacker* that attempts to intersect packets. In practice, minimizing the impact of an attack is equivalent to minimizing the impact of a worst-case failure.

We consider zero-sum games in which routers target at minimizing the time it takes for a packet to be safely transmitted, while the attacker's goal is to maximize this time. Therefore, the adversary attempts to intercept the packet at particular links (or nodes) in the network. It is well known from the game theory literature that the solution to such games requires the use of mixed (randomized) policies (cf., e.g., [13]). In practice, the mixed solution of the minimax problem provides the probability distributions needed for the next-hop probabilities. By formalizing the problem as an optimization with a time cost, we achieve both delivery and timeliness. Statistical flooding is a consequence of the saddle solution.

There are several alternatives to formalize a game that results in adequate routing policies. In this paper, we consider two alternatives: *off-line routing games* and *on-line games*.

In *off-line games*, the attacker starts by selecting one link or one physical interface at a particular node that she will scan for packets. This choice is made before routing starts but is not conveyed to the router, whose task it to design the next-hop probabilities to minimize the overall probability that the packet will be intercepted, assuming that the attacker made an intelligent choice. This setup can be generalized to attacks at nodes and even mixed attacks at both nodes and links. We shall see that the computation of routing policies for on-line games amounts to solving a linear program, requiring information about the overall network topology as in link-state routing.

In *on-line games*, the attacker is not forced to select a single link/node before routing starts. Instead, the attacker is allowed to scan one physical interface at every node. However, she will not be able to catch all packets that travel through the interface selected, only a fraction of these. For highly secure nodes this fraction would be zero, whereas it would have high values for less secure nodes. The computation of the routing policies that arise from this game can be done using dynamic programming, amenable to distributed computation as in distance vector routing.

It is important to emphasize that the abstract games described above *are not intended to represent realistic attack scenarios*, they mostly intend to capture the facts that (1) simultaneous failures in multiple links/nodes are unlikely and therefore one should optimize routing for robustness against a finite number of worst-case faults and that (2) an attacker will (hopefully!) have a finite set of resources available. Moreover, we will show that the attack models described above provide computational tools to obtain stochastic routing polices with adequate properties. Similarly, although the number of hops is generally a poor measure of routing-path quality, minimum-hop optimization is a useful tool to compute deterministic routing tables because it generally provides adequate routing trees.

As with deterministic routing, topology changes require the re-computation of the next-hop probabilities, regardless of the type of game considered. Failure to do so will generally result in lost packets. However, with stochastic routing some degree of functionality is preserved even before the next-hop probabilities are updated. This is because some of the packets will still make it through, as long as at least one of the paths from source to destination remains viable.

A. Stochastic routing policies

We consider a data transmission network with nodes $\mathcal{N} := \{1, 2, \dots, n\}$ connected by unidirectional links. We denote by $\mathcal{L}$ the set of all links and use the notation $\vec{ji}$ to represent a link from node j to node i. We assume that all the nodes in the network are connected in the sense that it is possible to reach any node from any other node through a finite sequence of links. The source and destinations nodes are denoted by n_{src} and n_{end}, respectively.

In a general stochastic routing framework, each stochastic routing policy is characterized by a list of probabilities $R := \{r_\ell : \ell \in \mathcal{L}\}$, such that

$$\sum_{\ell \in \mathcal{L}[k]} r_\ell = 1, \quad \forall k \in \mathcal{N}, \tag{1}$$

where the summation is taken over the set of links $\mathcal{L}[k] \subset \mathcal{L}$ that exit from node k. Under this policy, when a packet arrives at a node $k \in \mathcal{N}$, it will be routed with probability r_ℓ through the link $\ell := \overrightarrow{k\,k'} \in \mathcal{L}$ to the next-hop node k'. The distribution $\{r_\ell : \ell \in \mathcal{L}[k]\}$ determines the entries of the next-hop probabilities at node k, associated with the path from node n_{src} to node n_{end}. In this case, the routing table will actually be a matrix, as the next-hop may depend not only on the final destination node n_{end} but also on the source node n_{src}.

In the sequel, we denote by $\mathcal{R}_{\text{sto}}$ to be the set of lists that satisfy (1) and therefore $\mathcal{R}_{\text{sto}}$ represents the set of all stochastic routing policies. In this paper, we mostly consider *cycle-free* routing policies, i.e., policies for which a packet will never pass through the same node twice. Formally, $R \in \mathcal{R}_{\text{sto}}$ is cycle-free when there is no sequence of links

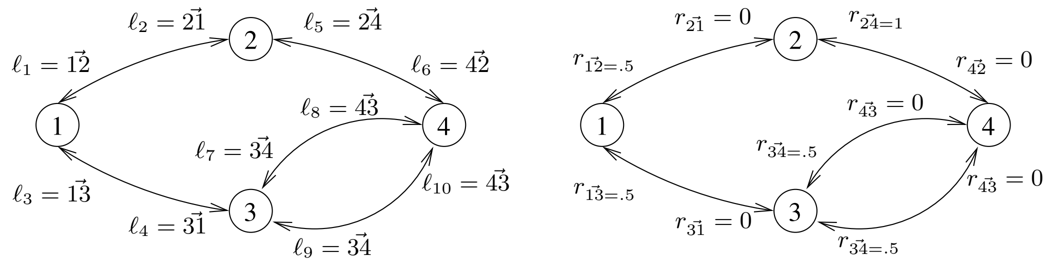
$$\mathcal{S} := \{\overrightarrow{k_1 k_2}, \overrightarrow{k_2 k_3}, \ldots, \overrightarrow{k_{k-1} k_k}, \overrightarrow{k_k k_1}\} \subset \mathcal{L}, \tag{2}$$

with positive probabilities $r_\ell > 0$ for all $\ell \in \mathcal{S}$ starting and ending at the same node k_1. We denote by $\mathcal{R}_{\text{no-cycle}}$ the subset of $\mathcal{R}_{\text{sto}}$ consisting of cycle-free policies.

Example 1: Figure 2(a) shows a 4-node/10-link example network with the corresponding sets $\mathcal{N}$ and $\mathcal{L}$. In this network all connections between the nodes are assumed bidirectional, which corresponds to two unidirectional links between every two nodes that are connected. Figure 2(b) shows an example of a stochastic routing policy from the source node 1 to the destination node 4. Under this policy, at each node the packets are routed with equal probability among the possible options. This policy is cycle-free. □

B. On-line games

In on-line games, the attacker has the capability of scanning a certain percentage of packets that go through every node. She then has to decide on which physical interfaces she should concentrate her efforts. For each node $k \in \mathcal{N}$, we denote by p_k the total percentage of packets that the attacker can scan on node k.



(a) (b)

Fig. 2. Example of (a) a network with 4 nodes $\mathcal{N} := \{1, 2, 3, 4\}$ and 10 links $\mathcal{L} := \{\ell_1, \ell_2, \dots, \ell_{10}\}$ and (b) a cycle-free stochastic routing policy from the node $n_{\text{src}} = 1$ to node $n_{\text{end}} = 4$.

In the context of on-line games, a *stochastic attack policy* is a list of probabilities $A := \{a_\ell : \ell \in \mathcal{L}\} \in \mathcal{R}_{\text{sto}}$ that specifies which percentage of packets will be scanned on each output interface of each node. The probability of a packet being scanned in the node k interface connected to the link $\ell := \overrightarrow{k\,k'} \in \mathcal{L}$ is therefore given by $p_k\, a_\ell$. Since $A \in \mathcal{R}_{\text{sto}}$, all probabilities a_ℓ that exit node k must add up to one, and therefore the total percentage of packets scanned in node k is indeed p_k. The selection of links by the router is done according to a stochastic routing policy $R := \{r_\ell : \ell \in \mathcal{L}\} \in \mathcal{R}_{\text{sto}}$ as described before.

For each link $\ell \in \mathcal{L}$, we denote by $\tau_\ell > 0$ the time it takes for a packet to transverse it assuming that it was not intercepted. When there is interception we assume that this time increases by T_ℓ. Denoting by $\mathbf{T}^*$ the amount of time that takes a packet to get from the source node n_{src} to the destination node n_{end}, the router selects a stochastic routing policy $R \in \mathcal{R}_{\text{sto}}$ so as to minimize the expected value of $\mathbf{T}^*$, whereas the attacker selects a stochastic attack policy $A \in \mathcal{R}_{\text{sto}}$ to maximize it. The problem just formulated is a zero-sum game for which we will attempt to find an optimal saddle pair of policies $R^* \in \mathcal{R}_{\text{sto}}$, $A^* \in \mathcal{R}_{\text{sto}}$ for which

$$\mathrm{E}_{R^*,A^*}[\mathbf{T}^*] = \min_{R \in \mathcal{R}_{\text{sto}}} \max_{A \in \mathcal{R}_{\text{sto}}} \mathrm{E}_{R,A}[\mathbf{T}^*] = \max_{A \in \mathcal{R}_{\text{sto}}} \min_{R \in \mathcal{R}_{\text{sto}}} \mathrm{E}_{R,A}[\mathbf{T}^*], \tag{3}$$

In the above equation, the subscripts on the expected value E emphasize the fact that the expectation depends on the routing/attack policies. The choice of a routing policy R^* for which (3) holds guarantees the *best possible timeliness (smallest* $\mathbf{T}^*$*), assuming an intelligent attacker that does her best to prevent this*. This is achieved by statistical flooding, as not fully exploring the available paths would be used by the attacker to her advantage.

The computation of the optimal routing and attack policies can be done using dynamic programming. To this effect, for each node $k \in \mathcal{N}$ we denote by V_k^* the *optimal cost-to-go from node* k, which is the average time it takes to send a packet from node k to node n_{end} using optimal policies for each player. Once the optimal costs-to-go have been computed for all nodes, the optimal routing policy can be computed as follows: for each node k, the next-hop routing distribution $\{r_\ell^* : \ell \in \mathcal{L}[k]\}$ over the set of links $\mathcal{L}[k]$ that exit node k is the solution to the following minimization:

$$\operatorname*{arg\,min}_{\substack{r_\ell:\ell\in\mathcal{L}[k]\\ \sum_\ell r_\ell=1}} \max_{\substack{a_\ell:\ell\in\mathcal{L}[k]\\ \sum_\ell a_\ell=1}} \sum_{\vec{ki},\vec{kj}\in\mathcal{L}[k]} r_{\vec{ki}} a_{\vec{kj}} m_{ijk}^*, \quad m_{ijk}^* := \begin{cases} V_i^* + \tau_{\vec{ki}} & i \neq j,\ k \neq n_{\text{end}} \\ V_i^* + \tau_{\vec{ki}} + p_k T_{\vec{ki}} & i = j,\ k \neq n_{\text{end}} \\ 0 & k = n_{\text{end}} \end{cases} \tag{4}$$

The optimal costs-to-go V_k^* can be computed with the help of the following function T that transforms a vector of costs-to-go $V := [V_1\ V_2\ \cdots\ V_N]$ into another vector of costs-to-go $V' := [V_1'\ V_2'\ \cdots\ V_N'] = T\big([V_1\ V_2\ \cdots\ V_N]\big)$, where the kth element V' is given by

$$V_k' = \min_{\substack{r_\ell:\ell\in\mathcal{L}[k]\\ \sum_\ell r_\ell=1}} \max_{\substack{a_\ell:\ell\in\mathcal{L}[k]\\ \sum_\ell a_\ell=1}} \sum_{\vec{ki},\vec{kj}\in\mathcal{L}[k]} r_{\vec{ki}} a_{\vec{kj}} m_{ijk}, \quad m_{ijk} := \begin{cases} V_i + \tau_{\vec{ki}} & i \neq j,\ k \neq n_{\text{end}} \\ V_i + \tau_{\vec{ki}} + p_k T_{\vec{ki}} & i = j,\ k \neq n_{\text{end}} \\ 0 & k = n_{\text{end}} \end{cases} \tag{5}$$

We defer to Section III-B.2 how these optimizations can be performed and proceed to state several important properties of the policies just defined (refer to the Appendix for their proofs).

Theorem 1: Assume that all the $\tau_\ell > 0$, $\ell \in \mathcal{L}$. Then

1) The vector $V^* := [V_1^*\ V_2^*\ \cdots\ V_N^*]$ of optimal costs-to-go is the unique fixed point of the function T defined by (5).
2) For any (not necessarily optimal) vector of costs-to-go $V(0)$, the optimal costs-to-go can be obtained by $V^* = \lim_{i\to\infty} \underbrace{T(T(\cdots(T}_{i \text{ times}}(V(0)))\cdots)$.
3) The stochastic routing policy $R^* \in \mathcal{R}_{\text{sto}}$ defined by (4) and the stochastic attacker policy $A^* \in \mathcal{R}_{\text{sto}}$ defined by a similar expression with the min and max interchanged form a saddle point-pair for the game, i.e., (3) holds.

1) Heterogeneous attacks: By choosing distinct percentages p_k for different nodes, we can take into account the fact that some nodes may be more secure than others. For instance, it would make sense to use non-homogeneous attack probabilities when connections pass through public and private networks, where the private nodes are assumed to be more secure than the public ones. In this case one would choose higher values for the percentages p_k for the nodes in the public network.

One can also encode in the p_k external information about where an attack is more likely to occur or succeed. In practice, by choosing high values for p_k, we are implicitly assuming that the node k is less secure. This information could be obtained, e.g., from intrusion detection sensors that provide indications where an attack may be occurring. In this case, the routing algorithm could actually adapt to the changing perception, as the intrusion detection sensors gain more confidence about which hosts have been compromised.

2) Computational issues: The minimax optimization needed to compute T in (5) can be solved using the following linear program: [13]

$$\begin{aligned} \frac{1}{V'_k} = \ & \text{maximum} \quad \sum_{\vec{ki}\in\mathcal{L}[k]} \tilde{r}_{\vec{ki}} \\ & \text{subject to} \quad \tilde{r}_{\vec{ki}} \geq 0, \quad \sum_{\vec{ki}\in\mathcal{L}[k]} \tilde{r}_{\vec{ki}} m_{ijk} \leq 1, \quad \forall \vec{kj} \in \mathcal{L}[k] \end{aligned} \tag{6}$$

The optimal next-hop routing distribution $\{r^*_\ell : \ell \in \mathcal{L}[k]\}$ over the set of links that exit node k can be obtained from $r^*_{\vec{ki}} = \frac{\tilde{r}_{\vec{ki}}}{\sum_{\vec{kj}\in\mathcal{L}[k]} \tilde{r}_{\vec{kj}}}$, where the $\tilde{r}_{\vec{ki}}$ are the solution to a linear program like (6), with the m_{ijk} replaced by the m^*_{ijk} in (4).

According to Statement 2 of Theorem 1, one can obtain the vector of optimal costs-to-go $V^* := [V_1^* \ V_2^* \ \cdots \ V_N^*]$ using an iteration of the form $V(i+1) = T\big(V(i)\big)$, where T is the function defined by (5) and the initial vector of costs-to-go $V(0)$ can be anything, e.g., equal to zeros for every node. In general, V^* is only obtained as $i \to \infty$ but one can usually stop the iteration after a finite number of steps, at the expense of getting a slightly sub-optimal policy. Typically, the iteration is stopped when there is a small change in $V(i)$. The number of steps needed is usually on the order of the maximum diameter of the graph.

The computation of the kth element of the vector of costs-to-go $V(i+1)$ can be performed at the node k provided that this node knows the elements of the vector $V(i)$ that correspond to their neighbors. Thus, the computation can be distributed in the same way that RIP is. However, in RIP or similar distance vector routing computations, at each stage the router performs an operation with complexity $O(d)$, where d is the out-degree of the router. In the case of on-line games, the router must solve a linear programming problem with worst-case complexity $O(d^3)$, but for which there are methods that typically require much more modest complexity.

Example 2: Figure 3 shows a stochastic routing policy obtained for an on-line game. In this example, the percentages p_k of packets scanned at each node where all set to 10%. This is consistent with a network where all nodes are equally secure. The left diagram shows the routing policy obtained when one selects $T_\ell \approx 0$, $\forall \ell \in \mathcal{L}$, i.e., when interception poses no penalty. In this case, one obtains exactly Equal-Cost Multi-Path routing [10] with hop count as the metric. In the right diagram, we see the case $T_\ell = 100$, $\forall \ell \in \mathcal{L}$. In this case, there is a heavy penalty incurred when a packet is intercepted and therefore routing favors maximal flooding, utilizing all possible paths. The middle diagram shows the intermediate case ($T_\ell = 45$, $\forall \ell \in \mathcal{L}$). Note that the link from node 7 to node 10 is not utilized while the link from node 7 to node 3 is. The reason for this is that while node 3 is no closer to the destination than node 10, there are many alternate paths from node 3 to the destination, while there is only one path from node 10 to the destination. The presence of alternate paths clearly makes the attacker's task more difficult. Therefore, from the defender's perspective, node 3 is more appealing than node 10. The path $\{7, 6, 9\}$ is similar to the path $\{7, 10, 2, 9\}$ in that once node 6 or node 10 is selected, the rest of the path is deterministic. However, the path $\{7, 6, 9\}$ is shorter. Hence, under no circumstances would the path $\{7, 10, 2, 9\}$ be selected. These results should be compared to the off-line example in the next section. $\square$

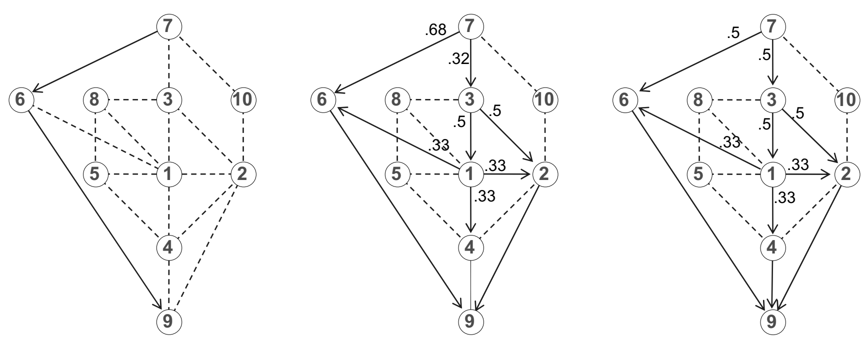


Fig. 3. Examples of routing policies obtained for an on-line game. When the probability of traversing a link is not zero or one, the probability is labeled near to the source end of the link. Dashed links are not used by the policies. The total percentage of packets scanned at each node was set to 10% and the destination is the bottom node labeled 9. The left diagram was obtained for $T_\ell \approx 0$, $\forall \ell \in \mathcal{L}$; the middle one for $T_\ell = 45$, $\forall \ell \in \mathcal{L}$; and the right one for $T_\ell = 100$, $\forall \ell \in \mathcal{L}$.

C. Off-Line Games

In off-line games the attacker is only allowed to select a single link for scanning and this choice must be done ahead of time. As in on-line games, we assume that the attacker may not posses sufficient resources to scan every packet in the link selected. To this effect, we take as given percentages of the packets p_ℓ, $\ell \in \mathcal{L}$ that the attacker would be able to scan if she were to select link ℓ. By choosing different percentages for different links we can take into account the fact that some links may be more secure than others. This formulation will shortly be extended to node-attacks as opposed to link attacks.

Assuming that there is more than one independent path from source to destination, the optimal action for the attacker is never to select a specific link to be scanned all the time. Otherwise, the router could simply avoid that link. Instead, the optimal policy for the attacker is to select links according to some distribution. In the context of off-line games a *stochastic attack policy* $A = \{a_\ell : \sum_\ell a_\ell = 1, \ell \in \mathcal{L}\}$ consists of a distribution over the set of links $\mathcal{L}$, where a_ℓ denotes the probability that the attacker will scan link ℓ. We denote by $\mathcal{A}$ the set of all stochastic attack policies, i.e., the set of distributions over $\mathcal{L}$.

In off-line games the router selects a cycle-free stochastic routing policy $R \in \mathcal{R}_{\text{no-cycle}}$ so as to minimize the probability of a packet being intercepted, whereas the attacker selects a stochastic attack policy $A \in \mathcal{A}$ so as to maximize it. Denoting by $\boldsymbol{\chi}$ a random variable that takes the value one when a when a packet is intercepted and zero otherwise, the problem just formulated is a zero-sum game for which we will attempt to find an optimal saddle pair of policies $R^* \in \mathcal{R}_{\text{no-cycle}}$, $A^* \in \mathcal{A}$ for which

$$\mathrm{E}_{R^*,A^*}[\boldsymbol{\chi}] = \min_{R \in \mathcal{R}_{\text{no-cycle}}} \max_{A \in \mathcal{A}} \mathrm{E}_{R,A}[\boldsymbol{\chi}] = \max_{A \in \mathcal{A}} \min_{R \in \mathcal{R}_{\text{no-cycle}}} \mathrm{E}_{R,A}[\boldsymbol{\chi}], \tag{7}$$

Note that the expected value of $\boldsymbol{\chi}$ is precisely the probability of a packet being intercepted. We will see shortly how this quantity can be computed from the values of the policies A and R.

The cost in (7) places no penalization on the number of links that a packet will cross from the source to the destination. However, in some cases one may want to favor shorter paths. This can be done by introducing a new random variable $\boldsymbol{\chi}_\epsilon$, $\epsilon \geq 0$ that is equal to zero in case the packet is not intercepted and equal to $(1+\epsilon)^{\mathbf{t}-1}$ when the packet is intercepted at the $\mathbf{t}$ hop.

Suppose now that we consider the zero-sum game

$$\mathrm{E}_{R^*,A^*}[\boldsymbol{\chi}_\epsilon] = \min_{R\in\mathcal{R}_{\text{no-cycle}}} \max_{A\in\mathcal{A}} \mathrm{E}_{R,A}[\boldsymbol{\chi}_\epsilon] = \max_{A\in\mathcal{A}} \min_{R\in\mathcal{R}_{\text{no-cycle}}} \mathrm{E}_{R,A}[\boldsymbol{\chi}_\epsilon] \tag{8}$$

For $\epsilon = 0$, $\boldsymbol{\chi}_\epsilon = \boldsymbol{\chi}$ and the cost is the same as in (7). However, for $\epsilon > 0$, (8) penalizes longer paths since the cost incurred increases as the number of hops increases. In fact, as $\epsilon \to \infty$ the potential burden of an extra hop is so large that the optimal solution will only consider paths for which the number of hops is minimal, leading to shortest path routing but not necessarily single-path. In the remainder of this section we consider the game in (8), as (7) is a special case of the former for $\epsilon = 0$.

To compute $\mathrm{E}_{R,A}[\boldsymbol{\chi}_\epsilon]$, we need to construct the matrix C that encodes the network connectivity. We define C to be a square matrix with one column/row per link, with the (ℓ_1, ℓ_2) entry equal to one if the link $\ell_2 = \vec{ij}$ ends at the node j where link $\ell_1 = \vec{jk}$ starts, and zero otherwise. We also define a column-vector s with one entry per link, which is equal to one if the corresponding link exits the source node n_{src} and zero otherwise. In the construction of C and s we should exclude all links that enter the source node n_{src} and exit the end node n_{end} as these links will never be used in cycle-free routing policies. The order in which the links are associated with the rows/columns of C and s must be consistent. The following result, proved in the Appendix, allows one to explicitly compute the value of $\mathrm{E}_{R,A}[\boldsymbol{\chi}_\epsilon]$.

Lemma 1: For given $\epsilon \geq 0$, $R \in \mathcal{R}_{\text{no-cycle}}$, $A := \{a_\ell : \sum_\ell a_\ell = 1, \ell \in \mathcal{L}\} \in \mathcal{A}$,

$$\mathrm{E}_{R,A}[\boldsymbol{\chi}_\epsilon] = \mathrm{row}[A]\, x, \tag{9}$$

where $\mathrm{row}[A]$ denotes a row-vector with one entry per link and $p_\ell a_\ell$ in the entry corresponding to the link $\ell \in \mathcal{L}$; x is the unique solution to

$$x = (1+\epsilon)\,\mathrm{diag}[R]Cx + \mathrm{diag}[R]s, \tag{10}$$

and $\mathrm{diag}[R]$ is a square diagonal matrix with the r_ℓ in the main diagonal.

The main difficulty in solving the routing game (8) is that the cost (9) is generally not convex on $R \in \mathcal{R}_{\text{no-cycle}}$. However, the relation specified by (10) between vectors x and policies R is in some sense one-to-one and will allow us to "convexify" the cost (9) by searching for "optimal" vectors x instead of policies R. To this effect, let C_{out} and C_{in} be matrices with one row per node and one column per link such that the entry of C_{out} corresponding the node k and link ℓ is equal to one if link ℓ *exits* node k and zero otherwise, and the entry of C_{in} corresponding the node k and link ℓ is equal to one if link ℓ *enters* node k and this is not the destination node n_{end} and equal to zero otherwise, i.e., $C_{\text{out}} := [\,c_{k,\ell}\,]$ and $C_{\text{in}} := [\,d_{k,\ell}\,]$ with

$$c_{k,\ell} := \begin{cases} 1 & \exists i \in \mathcal{N} : \ell = \vec{ki} \\ 0 & \text{otherwise,} \end{cases} \qquad\qquad d_{k,\ell} := \begin{cases} 1 & \exists i \in \mathcal{N} : \ell = \vec{ik},\ k \neq n_{\text{end}} \\ 0 & \text{otherwise.} \end{cases}$$

We further define s_{src} to be a column-vector with one entry per node with the entry corresponding to the source node n_{src} equal to one and all others equal to zero. In the construction of these matrices we should exclude all links that enter the source node n_{src} and exit the end node n_{end}. The following lemma establishes a one-to-one relation between the set of cycle-free stochastic policies (which is not convex in general) and a convex set. This will be the basis to find a solution to the routing game (8).

Lemma 2: Let $\mathcal{X}$ denote the convex set of vectors $x := \{x_\ell \geq 0 : \ell \in \mathcal{L}\}$ that satisfy

$$C_{\text{out}} x = (1+\epsilon) C_{\text{in}} x + s_{\text{src}}. \tag{11}$$

1) Given any $R \in \mathcal{R}_{\text{no-cycle}}$ there exists an $x \in \mathcal{X}$ for which

$$x = (1+\epsilon)\,\mathrm{diag}[R] C x + \mathrm{diag}[R] s \tag{12}$$

and the norms of the vectors $x \in \mathcal{X}$ can be bounded by a constant that is independent of $R \in \mathcal{R}_{\text{no-cycle}}$.

2) Given any $x := \{x_\ell \geq 0 : \ell \in \mathcal{L}\} \in \mathcal{X}$ that is cycle-free in the sense that there is no sequence of links (2) with $x_\ell > 0$, $\forall \ell \in \mathcal{S}$, there exists an $R := \{r_\ell :\in \mathcal{L}\} \in \mathcal{R}_{\text{no-cycle}}$ for which (12) holds, which is given by

$$r_\ell := \frac{x_\ell}{\sum_{\ell' \in \mathcal{L}[\ell]} x_{\ell'}}, \quad \forall \ell \in \mathcal{L}, \tag{13}$$

where the summation is taken over the set $\mathcal{L}[\ell]$ of links that exit from the same node as ℓ.

The equation (11) can be interpreted as a *flow-conservation law*, which states that the incoming flow to a node is equal to the outgoing flow from the same node, possibly amplified by $(1+\epsilon)$ when $\epsilon > 0$. Because of this we call the elements of $\mathcal{X}$ *flow vectors*.

We are now ready to state the main result of this section (proved in the Appendix), which provides the solution to off-line routing games. We defer to Section III-C.2 details on the computation of the optimal routing polices.

Theorem 2: For every $\epsilon \geq 0$, the routing game (8) has saddle-point policies. Moreover, the *flow-game* defined by

$$\text{row}[A^*]x^* = \min_{x \in \mathcal{X}} \max_{A \in \mathcal{A}} (\text{row}[A]x) = \max_{A \in \mathcal{A}} \min_{x \in \mathcal{X}} (\text{row}[A]x), \tag{14}$$

always has a saddle-point $(x^*, A^*) \in \mathcal{X} \times \mathcal{A}$ with x^* cycle-free, from which we can construct a saddle-point $(R^*, A^*) \in \mathcal{R}_{\text{no-cycle}} \times \mathcal{A}$ to original routing game (8), by computing R^* from x^* using (13).

1) Node-attack variations: While so far we focused our discussion on link attacks, one can easily solve the node attack problem by a suitable transformation of the network graph. When one wants to consider the possibility that one node can be attacked (or more precisely all the output interfaces of the node simultaneously) one simply expands the graph by unfolding the original node into two nodes, one that is fed by all the incoming links and another from which all outgoing links exit. The two new nodes are connected by a single link from the former to the latter that will carry all packets that pass through original node (cf. Figure 4). An attack on the so created "bottleneck" link in the new graph is equivalent to an attack to the node in the original graph. By choosing a suitable percentage of packets scanned p_ℓ in the new link, we effectively select the percentage of packets that can be scanned in the original node. The percentage of packets that can be scanned in the old links should be set to zero (unless one wants to consider mixed link-/node-attacks) and therefore the total number of link that are relevant for optimization actually decreases, making the problem computationally simpler.

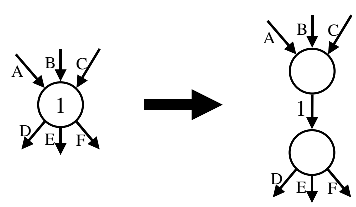


Fig. 4. Converting a node-attack to a link-attack. An attack on node 1 (left) is transformed into an attack on link 1 (right).

This approach can also be extended to simultaneous attacks to multiple links. Suppose, for example, that two ISPs lease a portion of the same physical link and each ISP represents its connection as a distinct logical link. Or similarly, suppose that distinct logical links in an overlay network correspond to the same physical link. In such situations, attacks to the physical link will result in an aggregate of logical links being attacked. The general problem of aggregate attacks is complicated by the fact the attacker may have the opportunity to catch a packet multiple times along its route. This issue has been dealt in some detail in [14].

2) Computational issues and max-flow/load-balancing problems: Theorem 2 allows us to compute saddle-points for the routing game (8) from saddle-points to the flow-game (14). It turns out that the latter game can be solved using a fairly standard technique to reduce the computation of

$$V^* = \min_{x \in \mathcal{X}} \max_{A \in \mathcal{A}} (\mathrm{row}[A]x) \tag{15}$$

to a linear-programing optimization. First note that because the cost is linear on A for fixed x, the inner optimization is always achieved at a distribution for which one of the a_ℓ is equal to one and all the others are equal to zero. Therefore, (15) is equivalent to[2]

$$V^* = \min_{x \in \mathcal{X}} \max_{\ell \in \mathcal{L}} (p_\ell \, x_\ell) = \min_{x \in \mathcal{X}} \min_{p_\ell \, x_\ell \le \mu, \, \forall \ell} \mu = \min_{\substack{0 \le p_\ell \, x_\ell \le \mu, \ \forall \ell \\ C_{\text{out}} x = (1+\epsilon) C_{\text{in}} x + s_{\text{src}}}} \mu. \tag{16}$$

Although (16) is already in the form of a linear program, it is instructive to reformulate it as a maximization by making the change of variables $\bar{\mu} := \mu^{-1}$ and $\bar{x} := \mu^{-1} x$:

$$\frac{1}{V^*} = \max_{\substack{0 \le p_\ell \, \bar{x}_\ell \le 1, \ \forall \ell \\ C_{\text{out}} \bar{x} = (1+\epsilon) C_{\text{in}} \bar{x} + \bar{\mu} s_{\text{src}}}} \bar{\mu}. \tag{17}$$

This shows that the value of the game is equal to the inverse of the maximum flow $\bar{\mu}$ from source to destination, consistent with the flow conservation law $C_{\text{out}} \bar{x} = (1+\epsilon) C_{\text{in}} \bar{x} + \bar{\mu} s_{\text{src}}$, and subject to the link-bandwidth constrains

$$\bar{x}_\ell \le \frac{1}{p_\ell}, \qquad \forall \ell \in \mathcal{L}. \tag{18}$$

Note also that, since $\bar{x}$ is simply a scaled version of x, the optimal routing policy can be computed directly from $\bar{x}$, using (13). This means that the routing policies that arise from the routing game (8) also *maximizes throughput subject to the constrain* (18). For $\epsilon = 0$ this turns out to be a standard max-flow problem, whereas for $\epsilon > 0$ we obtain a generalized max-flow with gain [15]. When this algorithm is applied to the transformed graph that encodes node-attacks, the maximum node-flow is minimized. This means that the policies arising from the routing

[2] In the second equality above, we used the fact that $\max\{\alpha_1, \alpha_2, \ldots, \alpha_k\} = \min_{\alpha_i \le \mu, \forall i} \mu$.

game (8) also achieve *load-balancing*. If the links and nodes have heterogeneous p_ℓ, then a weighted load-balancing is achieved.

The routing computations in (17) require that each node have knowledge of the entire topology, i.e., this is a link-state algorithm. However, it seems likely that a distributed approach is feasible. In particular, in the case that $\epsilon = 0$, there are several algorithms that solve the max-flow problem in a distributed fashion [16], [17]. The computational complexity of these algorithms is of order $O(n^2 m)$ where n is the number of nodes and m is the number of links. Furthermore, a hierarchical version of GTSR would likely yield significant computational saving.

Example 3: Figure 5 shows a stochastic routing policy obtained for an off-line game. In this example, the percentage p_ℓ of packets that the attacker could scan was assumed to be the same for every link ℓ. This is consistent with a network where all links are equally secure. The right diagram shows the routing policy obtained when one selects $\epsilon = 0$ and therefore delay is not penalized, leading to the maximal spreading of packets. In the left diagram, we see that when each extra hop corresponds to a severe cost penalty ($\epsilon = 100$), one obtains minimum-hop routing. The middle diagram shows an intermediate case ($\epsilon = .1$). In contrast to Figure 3, now the link from node 7 to node 10 is in general utilized because it is part of one of the three independent paths from source to destination. However, in on-line games, if a packet was sent through node 10 it was going to be caught with high probability since it necessarily had to be sent towards node 2 so this option was not considered. □

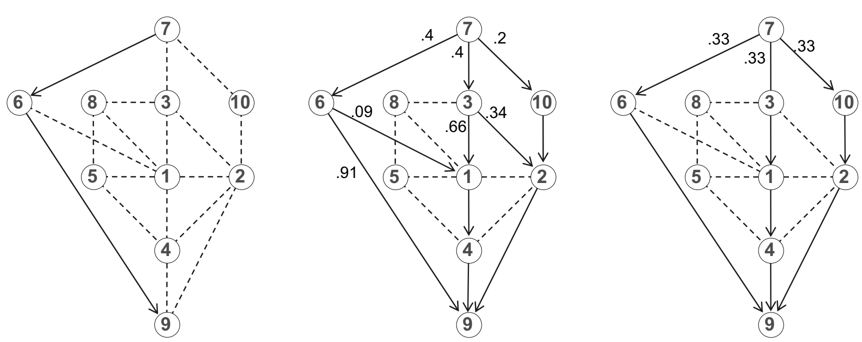


Fig. 5. Examples of routing policies obtained for an off-line game. When the probability of traversing a link is not zero or one, the probability is labeled near to the source end of the link. Dashed links are not used by the policies. The source is the top node labeled 7 and the destination is the bottom node labeled 9. The percentage of packets that the attacker could scan at each link was assumed to be the same for every link. The left diagram was obtained for $\epsilon = 100$, the middle one for $\epsilon = .1$, and the right one for $\epsilon = 0$.

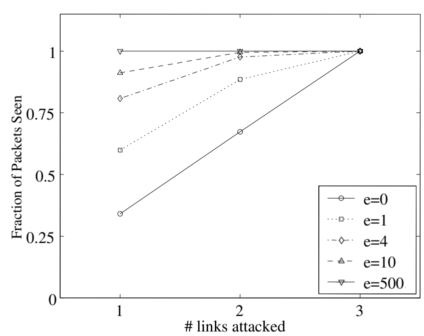
3) Routing tables vs. routing matrices: For on-line games without the back-to-start variation, the function T used to compute the optimal cost-to-go and eventually the optimal stochastic routing policies only depend on the destination node n_{end} and not on the source node n_{src}. In practice, this means that the optimal routing policies only depend on the final destination as in the usual deterministic routing algorithms such as RIP, OSPF, etc. However, for off-line games the matrices C_{in} and C_{out} used to compute the optimal routing policies depend both on the source and destination nodes (recall that we need to remove from these matrices the contribution of the nodes entering n_{src} and exiting n_{end}). In practice, this means that the routing tables will actually be matrices, as the choice of the probability distributions for the next-hop depends not only on the final destination node n_{end} but also on the source node n_{src}. A hierarchical approach would result in next-hop probabilities only depending on the source and destination prefix.

Another implementation approach is to use source routing whereby the end-hosts define the path to be taken by each packet and are then responsible for the randomization of paths. The Dynamic Source Routing (DSR) [18] protocol is an example of a source routing mechanism which has been proposed for use in multi-hop wireless ad-hoc networks (or MANETs). The use of source routing to enhance security has been previously suggested in [19].

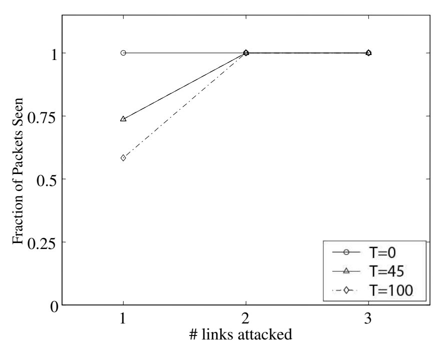
IV. Simulation Results

To evaluate the algorithm proposed in Section III applied to network layer routing, we simulated the network in Figures 3 and 5 using the `ns-2` network simulator [20]. In all simulations presented here, all links have propagation delay of 20ms and bandwidth of 10Mbps. Each queue implements drop-tail queuing discipline with maximum queue size set to 200 packets for the case of the CBR simulations and 100 packets for the TCP simulations. All packets are 1000 bytes long. The simulation time for each trial was 100 seconds. Two types of experiments were performed. In the first type only CBR traffic was used. In the second type, TCP-SACK traffic was used. In both types of experiments, the security parameter ϵ is fixed during a trial but varies from trial to trial.

We were interested in determining the effect of stochastic routing on reliability, throughput, and packet transmission delay. To evaluate how secure a particular routing policy is, we determine the maximum fraction of packets that an attacker could see by eavesdropping on one, two, or three links[3]. We assumed here that the attacker chooses the set of links that maximizes the fraction of packets seen (i.e., the "worst" case scenario). Figure 6 shows the simulation results obtained for off-line games with several values of the parameter ϵ and for on-line games with several values of the delay T_ℓ (the same for every link). Constant bit rate (CBR) traffic was used in all these simulations. As expected, routing is most secure for off-line games with $\epsilon = 0$, since in this case all paths are equally good and the packets will be spread the most across all paths. As ϵ increases, more packets are routed through the shorter paths and therefore an attacker eavesdropping on those will see a larger percentage of packets. In fact, for $\epsilon = 100$, we essentially have minimum-hop routing and by attacking a single link it is possible to see every packet. Because in the network tested there are only three independent paths, when the attacker is allowed to eavesdrop on three links she will be able to see every packet, regardless of which type of routing is used. On-line games generally do not result in maximum flow and in this particular topology explore at most two of the three independent paths. As mentioned before, this can be explained by the fact that node 10 is heavily penalized by on-line games for having a single output interface.



(a)



(b)

Fig. 6. Worst-case fraction of packets seen by an attacker eavesdropping on one, two, or three links, using off-line (a) and on-line (b) games (CBR traffic).

For off-line games with $\epsilon = 0$ we achieve maximum throughput (from a sender's perspective)

[3]This is equivalent to determining how reliable the routing policy is by examining the fraction of packets lost when one, two, or three links fail.

since we make use of all available paths (including the minimum cost one). This is supported by the data in Figure 7, where we plot the drop-rate as a function of the source's sending rate. For $\epsilon = 100$, drops start occurring at sending rates around 10Mbps, whereas, for $\epsilon = 0$, drops only become significant for sending rates higher than 30Mbps. Of course, the amount of throughput increase depends on the topology. The price to pay for security comes in terms of the average

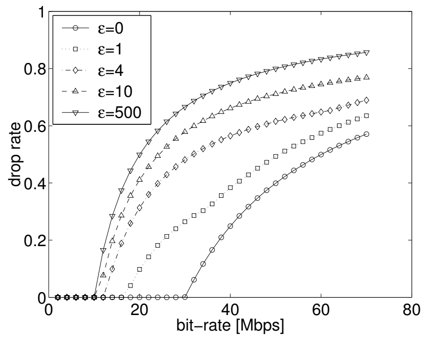


Fig. 7. Drop-rate vs. sending rate.

latency per packet. This is because to achieve high security one needs to explore all the paths from source to destination, including those with high latency. Figure 8 shows that for large ϵ we indeed have minimum average delay and as ϵ decreases the delay increases.

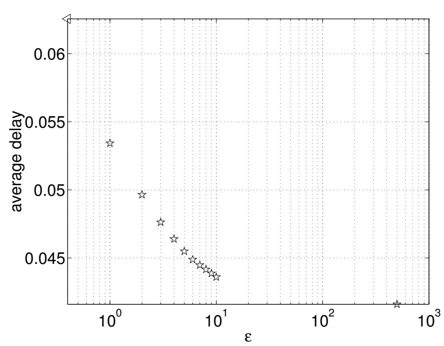
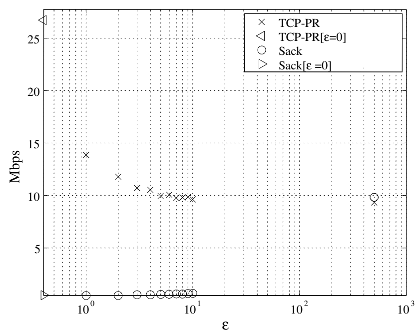


Fig. 8. Average packet transmission delay (CBR traffic). The triangle over the vertical axis corresponds to $\epsilon = 0$ (which could not be represented in log-scale).

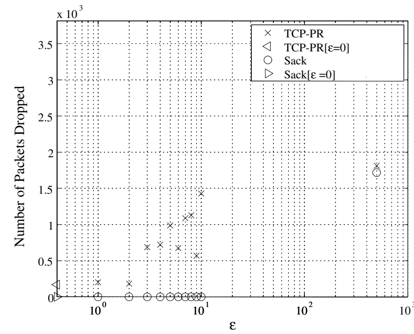
GTSR is well suited to "stop-and-wait" style protocols like the Trivial File Transfer Protocol (TFTP) [21]. By buffering data at the receiver, multimedia streaming applications can handle the increased delay (and delay variation). However, it turns out that problems arise when stochastic routing is used in conjunction with standard TCP (New Reno, SACK, etc.). Figure 9(a) shows the average throughput of a long-lived TCP-SACK (circles) and a modified version of TCP-SACK called TCP-PR (hash marks), both operating under stochastic routing. For the TCP-SACK, the throughput for $\epsilon = 100$ (essentially minimum-hop routing) is roughly six times larger than that for any other value of ϵ. This is because packets sent through longer paths are very often assumed dropped by TCP, as they only arrive after several packets that were sent later but traveled through shorter paths. Because fast-retransmit is only triggered when three duplicate acknowledgments are received, TCP-SACK is able to handle some degree of out-of-order packets. However, in all our simulations this proved insufficient to handle packets traveling through paths with distinct propagation times. The fact that standard TCP performs poorly when used in conjunction with multi-path routing has been observed in [11], [22].

TCP-PR was proposed in [23] and is one of several transport layers capable of coping with out-of-order packet delivery [24]. TCP-PR does not assume a packet is dropped when out-of-order sequence numbers are observed, but only when a time-out occurs. Figure 9(a) shows that in the case of $\epsilon = 0$, the throughput of the TCP-PR is larger than all other configurations. That is, the maximum security posture actually increases throughput as a by-product because it explores all alternative paths and, hence, uses all available bandwidth between the source and destination. Figure 9(b) shows the drop rate for the different TCP implementations and different ϵ. Figure 9(a) shows that for $\epsilon = 100$ (i.e., using shortest path routing), TCP-SACK and TCP-PR achieve essentially the same through-put.

A complete discussion of TCP-PR is beyond the scope of this paper. However, it was shown in [23] that TCP-PR and TCP-SACK compete fairly over a network that does not implement multi-path routing. Hence, it is possible to maintain a single transport layer that is compatible today's network and is also suitable for networks that implement stochastic routing. One implication of this is that multi-path routing could be incrementally deployed. For example, packets could be marked as being willing to be routed stochastically. Then, flows that use TCP-PR and multi-path routing would compete fairly with flows that request single path routing and use traditional implementations of TCP.



(a)



(b)

Fig. 9. Transmission rate (a) and drop rate (b) of TCP-SACK and TCP-PR for different security levels ϵ. For $\epsilon < 10$, the TCP-SACK flow experienced no drops. Since the x-axis is in logarithmic scale, the point $\epsilon = 0$ is indicated with an triangle on the y-axis.

V. CONCLUSIONS

In this paper we propose game-theoretic stochastic-routing (GTSR) and demonstrate through simulations that it improves routing security. By pro-actively forcing packets to probabilistically take alternate paths, stochastic routing mitigates the effects of interception, eavesdropping, and improves fault tolerance. The routing policies proposed proved efficient in achieving statistical flooding at the expense of some increase in average packet delay. A beneficial side-effect of these policies is an increase in throughput, as they explore multiple paths. The algorithms developed are applicable not only to the network layer, but also to application layer overlay networks, and multi-path transport protocols such as SCTP. However, when used with at the network layer, a transport layer that is robust to out-of-order packets such as TCP-PR [23] must be employed.

We presented two alternative techniques to generate multi-path routing tables. Routing based on off-line games maximizes the spread of packets across the network, but requires link-state information and generally results in routing matrices. Alternatively, routing based on on-line games does not achieve the same degree of statistical flooding, but the routing computation can be distributed as in distance-vector algorithms.

A direction for future investigation is the development of scalable algorithms to compute next-hop probabilities. One promising approach is to make use of hierarchical decomposition of routing. Since this type of approach generally yields sub-optimal routing policies, its impact on the GTSR performance requires further investigation. Preliminary results on the use of a hierarchical approach to compute routing tables based on off-line games will appear in [25]. Alternatively, on-line games can be implemented under distance-vector routing and are scalable. For these algorithms, questions related to convergence need to be investigated.

Appendix

A. Appendix—Derivations for on-line games

Proof of Theorem 1. The routing of the packet can be regarded as a controlled Markov chain, whose state $q_t \in \mathcal{N}$ is a random variable denoting the node where the packet is before the hop $t \in \{0, 1, 2, \dots\}$. For a given routing policy $R := \{r_\ell : \ell \in \mathcal{L}\} \in \mathcal{R}_{\text{sto}}$ and attack policy $A := \{a_\ell : \ell \in \mathcal{L}\} \in \mathcal{R}_{\text{sto}}$, the transition probability function for the Markov chain is given by $P(q_{t+1} = k' \mid q_t = k) = r_{\vec{kk'}}$, $\forall t \geq 0$. Without loss of generality we assume that the final node n_{end} is an absorbing state, i.e., that $P(q_{t+1} = n_{\text{end}} \mid q_t = n_{\text{end}}) = 1$, $\forall t \geq 0$. The cost to be optimized can be written as $\mathrm{E}_{R,a}[\mathbf{T}^*] = \mathrm{E}_{R,A}\left[\sum_{t=0}^{\infty} c(q_t)\right]$, where

$$c(k) = \sum_{\vec{ki},\vec{kj} \in \mathcal{L}[k]} r_{\vec{ki}} a_{\vec{kj}} m_{ijk}, \qquad m_{ijk} := \begin{cases} \tau_{\vec{ki}} & i \neq j,\ k \neq n_{\text{end}} \\ \tau_{\vec{ki}} + p_k T_{\vec{ki}} & i = j,\ k \neq n_{\text{end}} \\ 0 & k = n_{\text{end}} \end{cases}$$

The two-person zero-sum game just defined falls in the class of stochastic shortest path games considered in [26]. In particular, it satisfies the SSP assumptions: [SSP1] There exists at least one proper policy for the minimizer, i.e., a policy that will lead to a finite cost regardless of the policy chosen by the maximizer. This is true because we assume that there exists a sequence of link that connects node n_{src} to node n_{end}. [SSP2] For any policies for which there is a positive probability that the packet will not reach the destination node, the corresponding cost is infinite. This is true provided that $\tau_\ell > 0$, $\forall \ell \in \mathcal{L}$, because every hop that does not reach the final node n_{end} will contribute to the final cost with a positive marginal cost.

Consider now the function T defined by (5) and another function $\tilde{T}$ defined similarly, except that the $\max$ and $\min$ in (5) appear in the reverse order. These functions satisfy the regularity assumptions in [26]: [R1] The sets over which the controls $\{a_\ell : \ell \in \mathcal{L}[k]\}$, $\{r_\ell : \ell \in \mathcal{L}[k]\}$ take values are compact for every $k \in \mathcal{N}$. [R2] The maps from the controls $\{a_\ell : \ell \in \mathcal{L}[k]\}$, $\{r_\ell : \ell \in \mathcal{L}[k]\}$ to the transition probabilities $r_{\vec{kk'}}$ and the costs $c(k)$ are continuous for every

$k \in \mathcal{N}$. [R3-4] The minimum and maximum in the definitions of the functions T and $\tilde{T}$ are achieved and the two functions are actually equal [13, Minimax Theorem]. Statements 1 and 3 then follow from [26, Proposition 4.6] and statement 2 from [26, Proposition 4.7]. ■

B. Appendix—Derivations for off-line games

Proof of Lemma 1. Denoting by $x_\ell(t)$ the probability that a packet is routed through link $\ell \in \mathcal{L}$ at time $t \in \{1, 2, \dots\}$ and has not yet been intercepted, we have that for every $\ell \in \mathcal{L}$

$$x_\ell(1) = \begin{cases} r_\ell & \ell \in \mathcal{L} \text{ exits from node } n_{\text{src}} \\ 0 & \text{otherwise} \end{cases}, \tag{19}$$

$$x_\ell(t+1) = r_\ell \sum_{\ell' \in \mathcal{L}[\ell]} (1 - a_{\ell'} p_{\ell'}) x_{\ell'}(t) \quad \forall t > 1, \tag{20}$$

where the summation is taken over the set $\mathcal{L}[\ell]$ of links that enter the node from which link ℓ exits. Stacking all the $\{x_\ell : \ell \in \mathcal{L}\}$ into a column-vector x, we can write (19)–(20) as

$$x(1) = \text{diag}[R]\, s, \qquad x(t+1) = \text{diag}[R] C (I - \text{diag}[A]) x(t), \quad \forall t > 1, \tag{21}$$

where $\text{diag}[R]$ and $\text{diag}[A]$ denote diagonal matrices whose main diagonal contains the r_ℓ and the $a_\ell p_\ell$, respectively. From (21), we conclude that, for every $t \geq 1$,

$$x(t) = \big(\text{diag}[R] C (I - \text{diag}[A])\big)^{t-1} \text{diag}[R]\, s. \tag{22}$$

Since the probability that a packet is intercepted at time t is given by $\text{row}[A] x(t)$ and we can write $\text{E}_{R,A}[\boldsymbol{\chi}_\epsilon] = \sum_{t=1}^{\infty} (1+\epsilon)^{t-1} \text{row}[A] x(t)$. Moreover, because $x(t)$ evolves according to (22), we have that (9) holds with

$$x := \sum_{t=1}^{\infty} \big((1+\epsilon)\, \text{diag}[R] C (I - \text{diag}[A])\big)^{t-1} \text{diag}[R] s.$$

Since R is cycle-free, the above series only has a finite number of nonzero terms (at most one per hop). Therefore, it must converge and be equal to

$$\sum_{t=1}^{\infty} \big((1+\epsilon)\, \text{diag}[R] C (I - \text{diag}[A])\big)^{t-1} = \big(I - (1+\epsilon)\, \text{diag}[R] C (I - \text{diag}[A])\big)^{-1}$$

[27]. This means that $x = \big(I - (1+\epsilon)\, \text{diag}[R] C (I - \text{diag}[A])\big)^{-1} \text{diag}[R] s$, which is equivalent to (10). ■

Proof of Lemma 2. The convexity of $\mathcal{X}$ is trivial since $\mathcal{X}$ is given by the intersection of the (convex) positive orthant with the (also convex) affine space corresponding to the solution of the linear equation (11).

To prove 1, we show that for a given $R \in \mathcal{R}_{\text{no-cycle}}$ we can define

$$x := \sum_{t=1}^{\infty} \left((1+\epsilon)\,\mathrm{diag}[R]A\right)^{t-1} \mathrm{diag}[R]c. \tag{23}$$

First note that since $R \in \mathcal{R}_{\text{no-cycle}}$, the series converges because it only has a finite number of nonzero terms and therefore

$$\sum_{t=1}^{\infty} \big((1+\epsilon)\,\mathrm{diag}[R]A\big)^{t-1} = \big(I - (1+\epsilon)\,\mathrm{diag}[R]A)\big)^{-1}$$

[27]. From this and the definition of x we immediately conclude that (12) holds. To verify that the vector x defined by (23) belongs to $\mathcal{X}$ note that every entry of x is nonnegative because it is the sum of nonnegative numbers and also that left-multiplying (12) by C_{out} we obtain (11) because of the following two equalities that are straightforward to verify:

$$C_{\text{in}} = C_{\text{out}}\,\mathrm{diag}[R]C, \qquad s_{\text{src}} = C_{\text{out}}\,\mathrm{diag}[R]s. \tag{24}$$

Note also that because the number of nonzero terms in the series is always smaller than n and the R are bounded, one can construct a bound on the vectors x defined by (23), which is independent of $R \in \mathcal{R}_{\text{no-cycle}}$.

To prove 2 note that the division in (13) guarantees that the normalization condition (1) holds and therefore that $R \in \mathcal{R}_{\text{sto}}$. Moreover, this definition guarantees that if x is cycle-free then R is also cycle free. To finish the proof it remains to show that (12) holds. To this effect, note that from the definition of R, for every $\ell \in \mathcal{L}$ we have that $x_\ell = r_\ell \sum_{\ell' \in \mathcal{L}[k]} x_{\ell'} = r_\ell C_{\text{out}}[k]x$, where $\mathcal{L}[k]$ denotes that the set of links that exit from the node k from which ℓ exits, and $C_{\text{out}}[k]$ the row of C_{out} corresponding to the node k. But since $x \in \mathcal{X}$, we then have

$$x_\ell = (1+\epsilon) r_\ell C_{\text{in}}[k]x + r_\ell \delta_{k,n_{\text{src}}} \tag{25}$$

where $C_{\text{in}}[k]$ and denotes the rows of C_{in} corresponding to the node k and $\delta_{k,n_{\text{src}}}$ is equal to one if k is the source node n_{src} and zero otherwise. This finishes the proof because (12) is the vector version of (25). ∎

Proof of Theorem 2. First we can conclude from von Neummann's Theorem [13] that the flow-game (14) always has a saddle-point $(x^*, A^*) \in \mathcal{X} \times \mathcal{A}$, because the cost of the game is bilinear on the policies x and A, which take values in compact convex sets[4]. Moreover, since removing cycles from a policy never increases the cost, x^* can be assumed cycle-free.

Let then $(x^*, A^*) \in \mathcal{X} \times \mathcal{A}$ be the saddle-point whose existence was just proved. We show next that $(R^*, A*) \in \mathcal{R}_{\text{no-cycle}} \times \mathcal{A}$, with R^* is constructed from x^* using (13), is a saddle-point for the routing game (8). To this effect we need to show that

$$\mathrm{E}_{R^*,A}[\boldsymbol{\chi}_\epsilon] \leq \mathrm{E}_{R^*,A^*}[\boldsymbol{\chi}_\epsilon] \leq \mathrm{E}_{R,A^*}[\boldsymbol{\chi}_\epsilon], \tag{26}$$

for every $R \in \mathcal{R}_{\text{no-cycle}}$ and every $A \in \mathcal{A}$. Because of (9), equation (26) is actually equivalent to

$$\mathrm{row}[A]x^* \leq \mathrm{row}[A^*]x^* \leq \mathrm{row}[A^*]x, \tag{27}$$

where x is the unique solution to (10). To verify that x belongs to $\mathcal{X}$ note that left-multiplying (10) by C_{out} we obtain (11) because of (24). This means that (27) must hold because (x^*, A^*) is a saddle-point of the flow-game (14). ■

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