Scalable Testing of Context-Dependent Policies over Stateful Data Planes with Armstrong

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ABSTRACT

Network operators today spend significant manual effort in ensuring and checking that the network meets their intended policies. While recent work in network verification has made giant strides to reduce this effort, they focus on simple reachability properties and cannot handle context-dependent policies (e.g., how many connections has a host spawned) that operators realize using stateful network functions (NFs). Together, these introduce new expressiveness and scalability challenges that fall outside the scope of existing network verification mechanisms. To address these challenges, we present Armstrong, a system that enables operators to test if network with stateful data plane elements correctly implements a given context-dependent policy. Our design makes three key contributions to address expressiveness and scalability: (1) An abstract I/O unit for modeling network I/O that encodes policy-relevant context information; (2) A practical representation of complex NFs via an ensemble of finite-state machines abstraction; and (3) A scalable application of symbolic execution to tackle state-space explosion. We demonstrate that Armstrong is several orders of magnitude faster than existing mechanisms.

1 Introduction

Network policy enforcement has been and continues to be a challenging and error-prone task. For instance, a recent operator survey found that 35% of networks generate ≥ 100 problem tickets per month and one-fourth of these take multiple engineer-hours to resolve [18]. In this respect, recent efforts on network testing and verification (e.g., [20, 22]) offer a promising alternative to existing expensive and manual debugging efforts.

Despite these advances, there are fundamental gaps between the intent of network operators and the capabilities of these tools on two fronts: (1) data plane elements are complex and stateful (e.g., a TCP connection state in a stateful firewall) and (2) actual policies are context dependent; e.g., compositional requirements to ensure traffic is “chained” through services [20, 22] or dynamically triggered based on observed host behavior [21].

Together, stateful data planes and context-dependent policies introduce new challenges that fall outside the scope of existing network checking mechanisms [42, 43, 44, 63]. To understand why, it is useful to revisit their conceptual basis. Essentially, they capture network behavior by modeling each network function (e.g., a switch) as a “transfer” function $T(h, p)$ that takes in a located packet (a header $h$ and a port $p$) and outputs another located packet. Then, some search algorithm (e.g., model checking or geometric analysis) is used to reason about the composition of these $T$ functions. Specifically, we identify three key limitations with respect to expressiveness and scalability: (2):

- Packets are cumbersome and insufficient: While located packets allow us to compose models of NFs, they are inefficient to capture higher-layer processing semantics (e.g., proxy at HTTP level). Further, in the presence of dynamic middlebox actions [36], located packets lack the necessary context information w.r.t. a packet’s processing history and provenance, which are critical to reason about policies beyond reachability.
- Transfer functions lack state and context: The transfer abstraction misses key stateful semantics; e.g., reflexive ACLs in a stateful firewall or a NAT using consistent public-private IP mappings. Moreover, the output actions of NFs have richer semantics (e.g., alerts) beyond a located packet that determine the policy-relevant context.
- Search complexity: Exploring data plane behavior is hard even for reachability properties [42, 44, 63]. With stateful behaviors and richer policies, exploration is even more intractable and existing state-space search algorithms (e.g., model checking) can take several tens of hours even on small networks with ≤ 5 stateful NFs.

To address these challenges, we present a network testing framework called Armstrong (Figure 1). We adopt active data plane testing to complement static verification [20, 52, 63], because it gives concrete assurances about the behavior “on-the-wire” [63]. Armstrong takes in high-level network function $\text{impl}(\text{high-level policies})$ (e.g., proxy $\text{impl}(\text{high-level policies})$) as test cases to check the implementation of the policy.

Figure 1: Armstrong takes in high-level policy intent from the network operator and generates test cases to check the implementation of the policy.

1 A network function may be stateless (i.e., switches/routers) or stateful (i.e., middleboxes) and can be physical or virtual.
2 For concreteness, we borrow terminology from HSA [43]; other efforts share similar ideas at their core [42, 44, 46, 52].
policies from the operator, generates and injects test traffic into the data plane, and then reports if the observed behavior matches the policy intent. Note that Armstrong is not (and does not mandate) a specific policy enforcement system [9][39][53], rather it helps operators to check if the intended policy is implemented correctly.

Armstrong’s design makes three key contributions to address the expressiveness and scalability challenges:

- **ADU I/O abstraction (§5):** We propose a new Armstrong Data Unit (ADU) as a common denominator of traffic processing for network models. To improve scalability an ADU represents an aggregate sequence of packets; e.g., a HTTP response ADU coalesces tens of raw IP packets. Furthermore, an ADU explicitly includes the necessary packet processing context; e.g., an ADU that induced an alarm carries this information going forward.

- **FSMs-ensemble model for NFs (§6):** One might be tempted to use a NF’s code or a finite-state machine (FSM) model as a NF’s model, as they can capture stateful behaviors. However, these are intractable due to the huge number of states and transitions (or code paths). To ensure a tractable representation, we model complex NFs as an ensemble of FSMs by decoupling logically independent tasks (e.g., client-side vs. server-side connection in a NF) and units of traffic (e.g., different TCP connections).

- **Optimized symbolic execution workflow (§7):** For scalable test generation, we decouple it into two stages: (1) abstract test plan generation at the ADU granularity using symbolic execution (SE) because of its well-known scalability properties [30][31] and (2) a translation stage to convert abstract plans into concrete test traffic. We engineer domain-specific optimizations (e.g., reduce the number and scope of symbolic variables) to improve the scalability of SE in our domain.

We have written models for several canonical NFs in C and implement our domain-specific SE optimizations on top of KLEE. We prototype Armstrong as an application over OpenDayLight [13]. We implement simple monitoring and test validation mechanisms to localize the NF inducing policy violations (§9). Our evaluation (§10) on a real testbed reveals that Armstrong: (1) can test hundreds of policy scenarios on networks with hundreds of switches and stateful NFs nodes within two minutes; (2) dramatically improves test scalability, providing nearly five orders of magnitude reduction in time for test traffic generation relative to strawman solutions (e.g., using packets as NFs models I/O, or using model checking for search); (3) is more expressive and scalable than the state of the art; (4) effectively localizes intentional data/control plane bugs within tens of seconds.

### 2 Motivation

In this section, we use small but realistic network scenarios to highlight the types of stateful NFs and context-dependent policies used by network operators. We also highlight key limitations of existing network test/verification efforts. To make the discussion concrete, we use the transfer function and located packet abstraction from HSA [43]/ATPG [63], where each network NF (e.g., a switch) is a “transfer” function $T(h, p)$ whose input is a located packet (a header, port tuple) and outputs another located packet $h'$. The behavior of the network is the composition of such functions; i.e., $T_n(\ldots (T_2(T_1(h, p))))$. Our goal here is not to show the limitations of these specific efforts, but to highlight why the following scenarios fall outside the scope of this class of verification techniques (e.g., [42][44][47]).

#### 2.1 Stateful firewalling

While simple firewalls and OpenFlow ACLs have a simple match-action operation, real firewalls capture TCP session semantics. A common use is reflexive ACLs [4] shown in Figure 2 where the intent is to only allow incoming packets for established TCP connections that have been initiated from “internal” hosts. We depict the intended policy shown by a stateless transfer function $T(h, p)$. In particular, the $T$ behavior depends on the current state of the firewall for a given connection, and the function needs to update the relevant internal state variable. A natural extension is a finite-state machine (FSM) abstraction where $T(h, p, s)$ takes in a located packet and the current state, outputs a located packet, and updates the state. In this case, the state is per-session, but more generally it can span multiple sessions [39].

#### 2.2 Dynamic policy violations

Next, let us consider Figure 3 where the operator uses a proxy for better performance and also wants to restrict web access; e.g., $H_2$ cannot access to XYZ.com. As observed elsewhere [36], there are subtle violations that could occur if a cached response bypasses the monitoring device. Prior work has suggested many candidate fixes; e.g., better NF placement, tunnels, or new extended SDN APIs [35]. Our focus here is to check whether such policy enforcement mechanisms implement the policy correctly rather than de-

1For brevity, we assume no multicast/broadcast effects.
Figure 4: Are we firewalls correctly based on host?

As before, we need to model the stateful behavior of the proxy across connections, so let us consider our extended function $T(h, p, s)$. However, modeling the state alone is not sufficient. Specifically, the policy violations happen for cached responses, but this context (i.e., cached or not in this example) depends on some internal state variable inside the $T_{\text{proxy}}$ function. To faithfully capture the policy intent of the operator in our network model, we need to expose such relevant traffic’s processing history in our model. This suggests that we need to further extend the functions to include context as input $T(h, p, s, c)$ because the correct network behavior (e.g., downstream switches and middleboxes in our model) depends on this context. We formalized this definitions in §3.

This example also highlights several other issues. First, different NFs operate at different layers of the network stack; e.g., the monitoring device may operate at L3/L4 but the proxy in terms of HTTP sessions, which makes the “atomic” granularity at which their policy-relevant states/contexts manifest different. While it may be tempting to choose different granularities of traffic for different NFs, it means that we may no longer compose our $T$ functions if their inputs are different. Second, the policy-relevant context depends on a sequence of packets rather than on an individual packet. While it is not incorrect to think of $T$ functions operating on packets, it is not an efficient abstraction. Finally, note that just using headers is not sufficient as the behavior of the proxy depends on the actual content.

2.3 Firewalling with cascaded NATs

Figure 4 depicts a scenario inspired by prior work that showed cascaded NATs are error-prone [28,50]. Note that a correct NAT should use a consistent public-private IP mapping for a session [59]. To model such network behaviors, we need to both capture the packet provenance (i.e., where it originated from) and the consistent mapping semantics.

Unfortunately, existing tools such as HSA/ATPG essentially model stateful NFs as “black box” functions and do not capture or preserve the flow consistent mapping properties. This has two natural implications for our extended transfer function $T(h, p, s, c)$: (1) the context $c$ should also include the packet provenance, and (2) the function $T$ must be expressive enough to capture stateful NFs semantics (e.g., session-consistent mappings).

2.4 Multi-stage triggers

So far our examples underlined the need for capturing stateful semantics and relevant context inside a transfer function. We end this discussion with a dynamic service chaining example in Figure 5 that combines both effects. The intended policy is to use the light-weight IPS (L-IPS) in the common case (i.e., for all traffic) and only subject suspicious hosts flagged by the L-IPS (e.g., when a host generates too many scans) to the more expensive H-IPS (e.g., for payload signature matching). Such multi-stage detection is useful; e.g., to minimize latency and/or reduce the H-IPS load. Such scenarios are implemented today (albeit typically by hard-coding the policy into the topology) and enabled by novel SDN-based dynamic control mechanisms [9,23]. Unfortunately, we cannot check that this multi-stage operation works correctly using existing reachability mechanisms [43,63] because they ignore the IPSes states (e.g., the current per-host count of bad connections inside the L-IPS) and traffic context related to the sequence of intended actions.

Finally, note that the above examples have natural implications for a search strategy to explore the data plane behavior. Prior exhaustive search strategies were possible only because a transfer function processes each “header” independently and had no state. Thus they only had to search over the “header space”. Note that this is already hard and requires clever algorithms [63] and/or parallel solvers [64]. Designing a search strategy for the examples above is fundamentally more challenging because we need to consider a bigger “traffic” space (i.e., sequences of packets with payloads) and we need to efficiently explore a state space since processing of a packet by an NF (e.g., a stateful firewall) can change the behavior of the data plane for future packets.

2.5 Key observations

We summarize key expressiveness and scalability challenges that fall outside the scope of existing network verification abstractions and search strategies:

- NFs are stateful (e.g., §2.1) and have complex semantics beyond simple header match-action operations, and abstracting them as blackboxes is insufficient (e.g., §2.3);
- NF actions are triggered on sequences of packets and occur at different logical aggregations (e.g., §2.2);
- The correct behavior depends on traffic context such as provenance and processing history (e.g., §2.2 and §2.3);
3 Problem Formulation

In this section, we define the semantics of a stateful data plane using which we formalize a test trace to test the intended policies in a data plane. We then use these definitions to motivate the need for a model-based testing approach.

3.1 Data Plane Semantics

In this sub-section we formalize the semantics of stateful data planes and context-dependent policies. This formalization serves two purposes: (1) an understanding of the data plane semantics, where actual traffic is processed, provides insight into the methodology of generating test traffic; in particular, as we will see in this section, this formalization motivates the need for modeling the data plane to bridge the gap between a high-level policy and its manifestation in the data plane; (2) it serves as a reference point for the future research in the area of stateful data planes and context-dependent policies.

DPF: Since test traffic operates on the data plane level, in this sub-section we define the data plane semantics. First, we define the semantics of a NF and the network. Let \( \mathcal{P} \) denote the set of packets. Formally, a NF is a 4-tuple \( (S, I, E, \delta) \) where: (i) \( S \) is a finite set of states; (ii) \( I \) is the initial state; (iii) \( E \) is the set of network edges; and (iv) \( \delta : S \times \mathcal{P} \rightarrow S \times E 	imes \Sigma \) is the transition relation.

Here, \( \Sigma \) is a set of effects that capture the response of a NF to a packet. Each \( \alpha \in \Sigma \) provides contextual information that the administrator cares about. Each \( \alpha \) is annotated with the specific NF generating the effect and its relevant states; e.g., in Figure 3 we can have \( \alpha_1 = (LIPS : H_1, \text{Alarm}, \text{SendToHIPS}) \) when the LIPS raises an alarm and redirects traffic from \( H_1 \) to the H-IPS, and \( \alpha_2 = (LIPS : H_1, \text{OK}, \text{SendToInternet}) \) when the LIPS decides that the traffic from \( H_1 \) was OK to send to the Internet. Using effects, administrators can define high level policy intents rather than worry about low-level NF states. Note that this NF definition is general and it encompasses stateful NFs from the previous section and stateless L2-L3 devices.

Network: Formally, a network data plane \( net \) is a pair \( (N, \tau) \) where \( N = \{NF_1, \ldots, NF_N\} \) is a set of NFs and \( \tau \) is the topology map. Informally, if \( \tau(e) = NF_i \) then packets sent out on edge \( e \) are received by \( NF_i \). We assume that the graph has well-defined sources (with no incoming

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Policies in the data plane: Given the notion of trace semantics defined above, we can now formally specify our goal in developing Armstrong. At a high-level, we want to test a policy. Formally, a policy is defined as a pair \((\text{TraceSpec}; \text{TraceSem})\), where \(\text{TraceSpec}\) captures a class of traffic of interest, and \(\text{TraceSem}\) is the vector of effects of the form \((\alpha_1 \ldots \alpha_m)\) that we want to observe from a correct network when injected with traffic from that class. Concretely, consider two policies:

1. In Figure 3, we want: “Cached web responses to Dept1 should go to the monitor”. Then, \(\text{TraceSpec}\) captures web traffic to/from Dept1 and \(\text{TraceSem} = (\alpha_1, \alpha_2)\), with \(\alpha_1 = \text{Proxy : Dept1, CachedObject}\) and \(\alpha_2 = \text{Proxy : Dept1, SendToMon}\).

2. In Figure 3 we want: “If host H1 contacts more than 10 distinct destinations, then its traffic is sent to H - IPS”. Then, \(\text{TraceSpec}\) captures traffic from H1, and \(\text{TraceSem} = (\alpha_1, \alpha_2)\) where \(\alpha_1 = L - IPS : H1, Morethan10Scan\), and \(\alpha_2 = L - IPS : H1, SendToIPS\).

Test trace generation: Our goal is to check whether such a policy is satisfied by the actual network. More specifically, if we have a concrete test trace \(I\) that satisfies \(\text{TraceSpec}_{11}\) and should ideally induce the effects \(\text{TraceSem}_{11}\), then the network should exhibit \(\text{TraceSem}_{11}\) when \(I\) is injected into it. In other words, the goal of Armstrong in terms of test traffic generation is to find a concrete trace that satisfies \(\text{TraceSpec}_{11}\).

3.2 Challenges of automatic test traffic generation

The vision of Armstrong involves automating this test traffic (i.e., a set of test traces corresponding to all policies) generation. In an attempt to do so, however, we are facing two challenges. First, operators often define policies using a high-level representation, similar to what we saw in 2, as opposed to the complex form \((\text{TraceSpec}; \text{TraceSem})\) that involves low-level intricacies of each NF (i.e., \((S, I, E, D)\)). The challenge of test traffic generation is to follow. Given a policy, how to find concrete test traffic, out of very many possible distinct traces, that satisfies \(\text{TraceSpec}_{11}\).

In the next two sections we will discuss how Armstrong overcomes these challenges: (1) §6 will discuss how to NF models are used to bridge the gap between high-level policies and low-level data plane semantics; (2) §7 then will show how to systematically conduct search on the data plane model using symbolic execution to generate test traffic.

4 Armstrong Overview

In this section, we give an overview of Armstrong describing the key components and design ideas to address the challenges described at the end of the previous section.

Problem scope: Armstrong’s goal is to check if an operator’s intended policy is implemented correctly in the data plane. (Armstrong does not mandate a specific control- or data-plane policy enforcement mechanism [9, 26, 36, 49, 53], and our focus in this work is not on designing such a mechanism.) In this respect, there are two complementary classes of approaches: (1) Static verification (e.g., HSA [43], Veriflow [44], Vericon [26]) in which a model of the network is given to a verification engine that checks if the configuration meets the policy (or produces a counterexample); and (2) Active testing (e.g., ATPG [63]), where test traffic is injected into the network and check if the observed behavior is consistent with the intended policy. From a practical view, active testing can detect implementation problems that is outside the scope of static verification; a bug in the firewall implementation or the middlebox orchestration logic [39, 54]. Thus, we adopt an active testing approach in Armstrong. That said, our modeling contributions will also improve the scalability of static verification.

Scope of policies: For concreteness, we scope policies that Armstrong can (and cannot) check. In Armstrong, a policy is defined as a set of policy scenarios. A policy scenario is a 3-tuple \((\text{TraceSpec}; \text{policyPath}; \text{Action})\). \(\text{TraceSpec}\) specifies the traffic class (e.g., in terms of 5-tuple) to which the policy is related (e.g., srcIP=Dept, proto=TCP, and dstPort=80 in Figure 3), \(\text{policyPath}\) is the intended sequence of stateful NFs that the traffic needs to go through along with the relevant context (e.g., provenance=H2 and proxyContext=<hit,XYZ.com>) and \(\text{Action}\) is the intended final action (e.g., Drop) on any traffic that matches \(\text{TraceSpec}\) and \(\text{policyPath}\). The intended policy of Figure 3 captures three such different possibilities for the intended behavior, namely, one ending in action Allow, and two (i.e., for hit and miss) ending in action Drop when H2 tries to get XYZ.com, so the intended policy corresponds to three policy scenarios.

Other properties like checking performance, crash-freedom, infinite loops inside NFs, and race conditions are outside the scope of Armstrong. Similarly, if there are context/state behaviors outside the Armstrong models, then Armstrong will not detect those violations.

Design space and strawman solutions: Given the complexity of stateful NFs and context-dependent policies, it will be tedious for an operator to manually reason about their interactions and generate concrete test cases to check the data plane behavior. In a nutshell, the goal of Armstrong is to simplify the operators workflow so that they only need to specify high-level policy scenarios such as the policies from the previous section. Armstrong automatically generates test traffic to exercise each given policy scenario to simplify the process of validating if the data plane correctly implements the operator’s intention.

In a broader context, Armstrong is an instance of a specification-based or model-based testing paradigm [60]. Any model-based testing solution needs a to bridge the semantic gap between the high-level intended behavior of the system (in case of Armstrong, high-level policies and the actual system behavior (in case of Armstrong, running code
and hardware in the data plane). A specific solution can be viewed in terms of a design space involving three key components: (1) A basic unit of input-output (I/O) behavior; (2) A model of the expected behavior of each component; and (3) Some way to search the space of end-to-end system behaviors to generate test cases. We, therefore, can represent a point from the design space as a 3-tuple with specific designs for each component.

To see why it is challenging to find a solution that is both expressive and scalable, let us consider two points from this design space. At the one end of the spectrum, we have prior work like ATPG \cite{6} with: \(\langle I/O = \text{LocPkt}, \text{Model} = \text{Stateless}, \text{Search} = \text{Geometric}\rangle\). As argued earlier, these are not expressive. At the opposite end we consider running model checking on implementation source code and use packets as the I/O unit; i.e., \(\langle I/O = \text{Pkt}, \text{Model} = \text{Impl}, \text{Search} = \text{MC}\rangle\). While this can be expressive (modulo the hidden contexts), it is not scalable given that actual NF code can be tens of thousands of lines of code since model checking tools struggle beyond a few hundred lines of code. Furthermore, using a NF implementation code as its model is problematic, as it is not expressible (modulo the hidden contexts), it is not scalable given that actual NF code can be tens of thousands of lines of code since model checking tools struggle beyond a few hundred lines of code. Moreover, using a NF implementation code as its model is problematic, as implementation bugs can defeat the purpose of testing by affecting the correctness of test cases\footnote{There is also the pragmatic issue that we may not have the actual code for proprietary NFs.}

**High-level approach:** Our contribution lies in design choices for each of these three dimensions that combine to achieve scalability and expressiveness:

- \(I/O = \text{ADU} (\S\S):\) We introduce a novel abstract network data unit called an Armstrong Data Unit (ADU) that improves scalability of test traffic generation via traffic aggregation and addresses expressiveness by explicitly capturing relevant traffic context;
- \(\text{Model} = \text{FSM Ensemble} (\S\S):\) We model each NF as an ensemble of FSMs and compose them to model the data plane. Here, using FSMs as building blocks enables the stateful model and breaking a monolithic FSM into the ensemble dramatically shrinks the state space;
- \(\text{Search} = \text{Optimized Symbolic Execution} (\S\S):\) Given our goal is to generate test traffic, we can sacrifice exhaustive searching and use more scalable approaches like symbolic execution (SE) rather than model-checking. However, using SE naively does not handle large topologies and thus we implement domain-specific optimizations for pruning the search space.

Note that these decisions have natural synergies; e.g., ADUs simplify the effort to write NF models and also improves the scalability of our SE step.

**End-to-end workflow:** Putting these ideas together, Figure 6 shows Armstrong’s end-to-end workflow: The operator defines the intended network policies in a high-level form, such as the policy graphs shown on top of each figure of Figure 6. Armstrong uses a library of NF models, where each model works at the ADU granularity. Given the library of NF models and the network topology specification (with various switches and middleboxes), Armstrong constructs a concrete network model for the given network. Then, it uses the network model in conjunction with the policies to automatically generate concrete test traffic. Here, we decouple the test traffic generation into two logical steps by first running SE on the data plane model to generate abstract (i.e., ADU-level) test traffic and then using a suite of traffic injection libraries to translate this abstract traffic into concrete test traffic via test scripts. Finally, we use a monitoring mechanism that records data plane events and analyzes them to declare a test verdict to the operator (i.e., success, or a policy violation along with the NF in charge of the violation).

Note that operators do not need to be involved in the task of writing NF models or in populating the test generation library. These are one-time offline tasks and can be augmented with community efforts \cite{11}.

5 ADU Input-Output Abstraction

In this section, we present our ADU abstraction for modeling NF I/O operations and show how it enables scalability and expressiveness, while still acting as a common denominator across diverse NFs. We discuss the implications of this choice for the design of the NF models and our search strategy. We end the section with guidelines and a recipe for extending ADUs for future scenarios.

**Key ideas:** Concretely, an ADU is simply a struct as shown in Listing 1. Our ADU abstraction extends located packets from prior work in two key ways:

- **Traffic aggregation:** First, each ADU can represent a se-

```c
struct ADU{
  // IF fields
  int srcIP, dstIP, proto;
  // transport
  int srcPort, dstPort;
  // TCP specific
  int tcpSYN, tcpACK, tcpFIN, tcpRST;
  // HTTP specific
  int httpGetObj, httpRespObj;
  // Armstrong-specific
  int dropped, networkPort, ADUId;
  // Each NF updates traffic context
  int c-Tag[MAXTAG];
  ...
}
```

Figure 6: Armstrong workflow.

Listing 1: ADU structure.
queue of packets rather than an individual packet. This enables us to represent higher-layer operations more efficiently; e.g., state inside an NF (e.g., a TCP connection's current state on a firewall) is associated with a set of packets rather than a single IP packet. As another example, a proxy cache's state transitions to a new "relevant state" (i.e., cached state with respect to an object) only after the entire payload has been reassembled.

- **Explicitly binding the context**: Each ADU is explicitly bound to its relevant context through the c-Tags field. Conceptually, c-Tags ensure that the ADU carries its "policies-related processing history" as it goes through the network. The natural question is what should these c-Tags capture? Building on our insights from motivating examples of §2, c-Tags contain two types of information: (1) ADU's provenance (i.e., it's origin that may be otherwise hidden, for example, after a NAT), (2) NF processing context for the intended policies (e.g., 1 bit for cache hit/miss, 1 bit for alarm/no-alarm). Concretely, a c-Tag is the union of different fields to embed relevant context w.r.t. different NFs that the ADU has gone through and the ADU provenance.

**Implications for NF models and test generation**: The ADU abstraction has natural synergies and implications for both NF models and test traffic generation. First, ADUs help reduce the complexity of a NF's models by consolidating protocol semantics (e.g., HTTP, TCP) and effects involving multiple IP packets. For example, all packets corresponding to an HTTP reply are represented by one ADU with the httpRespObj field indicating the retrieved object id. Note in particular that the struct fields are a superset of required fields of specific NFs; each NF processes only fields relevant to its function (e.g., the switch function ignores HTTP layer fields of input ADUs—see §6). Second, w.r.t. our test traffic generation, by aggregating multiple packets, ADUs reduce the search space for model exploration tools such as SE (§7). That said, they introduce a level of indirection because the output of SE cannot be directly used as a test trace and thus we need the extra translation step before we can generate raw packet streams.

**Designing future ADUs**: Given the continued evolution of NFs and policies, a natural question is how can we extend the basic ADU. While we cannot claim to have an ADU definition that can encompass all possible network scenarios and policy requirements, we present a high-level design roadmap that has served us well. First, the key to determining the fields of an ADU is to identify policy-related network protocols in all NFs of interest. For example, each of TCP SYN, TCP SYN+ACK, etc. make important state transitions in a stateful firewall and thus should be captured as ADU fields. The key point here is that our ADU abstraction is future-proof; e.g., if we decide to add an ICMP field to the ADU of Listing 1 (e.g., because our new policy involves ICMP on some new NF models), this is not going to affect existing NF models, as they simply ignore this new field. The second point is to consider a conservatively large c-Tag field to accommodate various types of relevant traffic context (e.g., sufficient number of bits to allow representation of different types of IPS alarms, as opposed to having 1 bit for capturing alarm/no-alarm in c-Tag).

## 6 Modeling the Data Plane

In this section, we begin by exploring some seemingly natural strawman approaches to model each NF (§6.1) and then present our idea of modeling NFs as ensembles of FSMs by decoupling an NF's actions based on logically independent units of traffic and internal tasks (§6.2).

### 6.1 Strawman solutions

To serve as a usable basis for automatic test traffic generation, a NF model needs to be scalable, expressive, and amenable to composition for network-wide modeling. Given the composability requirement, we first rule out very "high-level" models such as writing a proxy in terms of HTTP object requests/responses [35]. This leaves us two options: using the code or the FSM abstraction we alluded to §2.

1. **Code as "model"**: This choice seems to remove the burden of explicit modeling, but such a model is too complex. For instance, Squid [16] has ≥ 200K lines of code and introduces other sources of complexity that are irrelevant to the policies being checked. Another fundamental issue with this choice would be that a bug in the to-be-tested implementation code affects the correctness of test traffic generated from such model! In summary, this approach yields expressive "models", but is not scalable for exploring the search space.

2. **Write an NF model as a monolithic FSM**: [2] already suggests that FSMs may be a natural extension to the stateless transfer functions. Thus, we can consider each NF as an FSM operating at the ADU granularity. That is we can think of the current state of a stateful NF as vector of state variables (e.g., in proxy this vector may have three elements: per-host connection state, per-server connection state, and per-object cache state). Again, this is not scalable; e.g., a stateful NF with S types of state with V possible values, means this "giant" FSM has V^S states.

Based on this discussion, we adopt FSMs as a natural starting point to avoid the logical problems associated with using code. Next we discuss how we address the scalability challenge.

### 6.2 Tractable models via FSM ensembles

Our insight is to borrow from the design of actual NFs. In practice, NF programs (e.g., a firewall) do not explicitly enumerate the full-blown FSM. Rather, they independently track the states for "active" connections. Furthermore, different functional components of an NF are naturally segmented; e.g., client- vs. server-side handling in a proxy is separate. This enables us to simplify a monolithic NF FSM into a more tractable ensemble of FSMs along two dimensions:
Figure 7: Illustrating how decoupling independent traffic units reduces number of states.

(a) A monolithic FSM model of a stateful firewall w.r.t two TCP connections.
(b) A per-connection FSM model of a stateful firewall.

Figure 8: Illustrating how decoupling independent NF tasks reduces number of states.

(a) A monolithic FSM model of a proxy w.r.t. a client, a server, and an object.
(b) A proxy model as an FSM ensemble, enabled by decoupling independent NF tasks.

- Decoupling independent traffic units: Consider a stateful firewall. The naive approach in modeling it as a monolithic FSM is shown in Figure 7a. While this is an expressive model, it is not scalable as the number of connections grows. We decouple this into independent per-connection FSMs as shown in Figure 7b, yielding the firewall model as an ensemble of FSMs.

- Decoupling independent tasks: To see this idea, consider a proxy which is instructive, as it operates on a session layer, terminates sessions, and it can respond directly with objects in its cache. The code of a proxy, e.g., Squid, effectively has three modules: TCP connections with the client, TCP connection with the server, and cache. The proxy FSM is effectively the “product” of these modules (Figure 8a). However, we can decouple different tasks; i.e., client-, server-side TCP connections, and cache. Instead of a “giant” FSM model with each state being of the “cross-product” form \(\langle\text{client\_TCP\_state}, \text{server\_TCP\_state}, \text{cache\_content}\rangle\), we use an ensemble of three small FSMs each with a single type of state, i.e., \(\langle\text{client\_TCP\_state}\rangle\), \(\langle\text{server\_TCP\_state}\rangle\), and \(\langle\text{cache\_content}\rangle\) (Figure 8b).

Listing 2: Proxy as an ensemble of FSMs.

```
ADU Proxy(NFId id, ADU inADU) {
    ... 
    if (!inADU) {
        if (isCmplt) {
            if (isHttpRq) {
                if (srvConnEstablished(id, inADU)) {
                    if (cached(id, inADU)) {
                        outADU = reqSrv(id, outADU); 
                    } else {
                        outADU = tcpSYNcSrv(id, inADU); 
                    }
                } else {
                    outADU = tcpSYNcSrv(id, inADU); 
                }
            } else {
                if (cached(id, inADU)) {
                    outADU = reqSrv(id, outADU); 
                } else {
                    outADU = tcpSYNcSrv(id, inADU); 
                }
            }
        } else {
            if (cached(id, inADU)) {
                outADU = reqSrv(id, outADU); 
            } else {
                outADU = tcpSYNcSrv(id, inADU); 
            }
        }
    } else {
        if (cached(id, inADU)) {
            outADU = reqSrv(id, outADU); 
        } else {
            outADU = tcpSYNcSrv(id, inADU); 
        }
    }
    return outADU;
```

Note that these ideas are complementary and can be combined to reduce the number of states. For instance, if our proxy is serving two clients talking to two separate servers, we can first decouple states at the task-level and further decouple the states within each task at the connection level.

To see this concretely, Listing 2 shows a partial code snippet of a proxy model, focusing on the actions when a client is requesting a non-cached HTTP object and the proxy does not currently have a TCP connection established with the server. Here the `id` allows us to identify the specific proxy instance.

The specific state variables of different proxy instances are inherently partitioned per NF instance (not shown). These track the relevant NF states, and are updated by the NF-specific functions such as `srvConnEstablished`.

If the input `inADU` is a client HTTP request (Line 3), and if the requested object is not cached (Line 4), the proxy checks the status of TCP connection with the server. If there is an existing TCP connection with the server (Line 5), the output `ADU` will be a HTTP request (Line 6). Otherwise, the proxy will initiate a TCP connection with the server (Line 8).

Context processing: The one remaining issue is the propagation and updation of the context information in our model network. As we saw in 15 each NF encodes the relevant context in the c-Tag field of the outgoing ADU (Line 12). For instance, if an NF modifies headers, then the ADU encodes the provenance of the ADU which can be used to check if the relevant policy at some downstream NF is implemented correctly. In summary, each NF is thus modeled as an FSM ensemble that receives an input ADU and generates an output ADU with the corresponding updated c-Tags.

6.3 Network-wide modeling

Given the per NF models, next we discuss how we compose these models to generate network-wide models. To make this discussion concrete, we use the network from Figure 3 and see how we compose the proxy, switch, and monitor models in Listing 3.

Each NF instance is identified by a unique id that allows us to know the “type” of the NF and thus index into the global variables is an implementation artifact of using C/KLEE, and is not fundamental to our design.

In general, if the number of connections is \(|conn|\) (2 in this example) and the number of states per connection is \(|state|\) (4 in this example), it is easy to see that this insight cuts the number of states from \(|state|^{|conn|}\) to \(|conn| \times |state|\).

Concretely, if an NF has \(|T|\) independent tasks (e.g., 3 for proxy) where the ith task has \(S_i\) states (e.g., 2 for the cache task in this example) the ensemble cuts down the number of states from \(\prod_{i=1}^{|T|} |S_i|\) to \(\sum_{i=1}^{|T|} |S_i|\).

This choice of passing “id”s and modeling the state in per-id global variables is an implementation artifact of using C/KLEE, and is not fundamental to our design.
relevant variables. Lines 8-11 model the stateless switch. Function lookUp takes the input ADU, looks up its forwarding table, and creates a new outADU with its port value set based on the forwarding table. Given the operators policy, parameters of the network and each NF model are configured. For example, given the policy of Figure 3, hostToWatch is set to H2. As another example, given the policy of Figure 5 the alarm threshold in the L-IPS is configured to 10. Following prior work [43], we consider each switch NF as a static data store lookup updating located packets. Lines 13-24 capture the monitoring NF. Given the actual network’s topology and the library of NFs models, this composition is completely automatic and does not require the operator to “write” any code. Given the network topology Armstrong can identify the instance of Next_DPF in line 34 of Listing 3.

Similar to prior work [43, 63], we consider a network model in which packets are processed in a one-packet-per-NF-at-time fashion. That is, do not model (a) batching or queuing effects inside the network, (b) parallel processing effects inside NFs or (c) simultaneous processing of different packets across NFs. Since our goal is to look for “policy” violations represented in terms of NF-context sequences, this assumption is reasonable. Based on this semantics, the data plane as a simple loop (Line 31). Note that because ADUs extend the located packet abstraction, they also capture the behaviors of the NF w.r.t. these required states and contexts; e.g., for a NAT we add per-flow consistent mapping behaviors. In doing so, we make sure to identify the opportunities for decoupling independent tasks and traffic units to enable the scalable ensemble representation. While we are not aware of automated tools for synthesizing middlebox models, recent advances in program analysis and software engineering might be a promising avenue for automating model synthesis (e.g., [27]).

### 6.4 Writing future NF models

We have manually written a broad range of NF models. While we do not have an algorithm for writing a NF model, we can provide design guidelines for writing future NF models based on our own methodology. We begin by enumerating the set of policy scenarios (e.g., as in the examples of §3); this enumeration step can be a broader community effort in future [11, 21, 29]. Across the union of these scenarios, we identify the necessary contexts (e.g., alarm, cache hit) and corresponding NF states that affect these contexts (e.g., TCP state machine of firewall, cache contents). This gives us a set of model requirements. Then for each type of NF, we start with a “dumb” switch abstraction and incrementally add the logic to the model to capture the expected behaviors of the NF w.r.t. these required states and contexts; e.g., for a NAT we add per-flow consistent mapping behaviors and packet provenance context. In doing so, we make sure to identify the opportunities for decoupling independent tasks and traffic units to enable the scalable ensemble representation. While we are not aware of automated tools for synthesizing middlebox models, recent advances in program analysis and software engineering might be a promising avenue for automating model synthesis (e.g., [27]).

### 7 Test Traffic Generation

In this section, we describe how we use the network-wide model and operator’s policy to generate concrete test traffic to exercise policy-relevant data plane states. For Armstrong to be interactive for operators, we want this step to be scalable enough to produce test plans within seconds to a few minutes even for large networks. Unfortunately, several canonical search solutions including model checking [5, 33]. AI graph planning tools [6] do not scale beyond networks with 5-10 stateful NFs; e.g., model checking took 25 hours for a network with 6 switches and 3 middleboxes. Next, we describe how we make this test generation problem tractable.
### 7.1 Symbolic execution for abstract test plans

**Why Symbolic Execution (SE)?** There are two key scalability concerns about test traffic generation. First, we need to search over a very large space of possible sequence of traffic units. While ADUs improve scalability as compared with IP packets via aggregation, we still have to search over the space of possible ADU value assignments. Second, the state space of the data plane is again very large. While the FSM ensembles abstraction significantly reduces the number of states, it does not address state space explosion due to composition of NFs; e.g., if the models of NF1 and NF2 can reach K1 and K2 possible states for some ADU, respectively, the composition can reach K1 × K2 states. The traffic- and state-space explosion makes our problem (even to find abstract test traffic) challenging.

To address this scalability challenge, we turn to **symbolic execution** (SE), which is a well-known approach in formal verification to address state-space explosion [30]. At a high level, an SE engine explores possible behaviors of a given program by considering different values of **symbolic variables** [31]. One concern is that SE sacrifices coverage. In our specific application context, this tradeoff to enable interactive testing is worthwhile. First, administrators may already have specific testing goals in mind. Second, configuration problems affecting many users will naturally manifest even with one test trace. Finally, with a fast solution, we can run multiple tests to improve coverage.

**Mapping policy to assertions:** For each policy scenario \((TraceSpec; policyPath; Action)\) of the operator’s policy \(\mathcal{P}\), Armstrong uses SE as follows. First, we constrain the symbolic ADUs to satisfy the condition. Second, we introduce the negation of policyPath, namely \(\neg(policyPath)\), as an assertion in the network model code. In practice, given the policy and network topology, Armstrong instruments the network model with \(\neg(policyPath)\) assertions expressed in terms of ADU fields (e.g., networkPort, c-Tag). Then, the SE engine finds an assignment to symbolic ADUs such that the assertion is violated. Because we use the negation in the assertion, in effect, SE concretizes a sequence of ADUs that induce policyPath in the network model. This abstract test traffic generated by SE, after being translated into concrete test traffic and injected into the actual data plane, must traverse NFs specified in policyPath and result in Action; otherwise, the policy scenario is incorrectly implemented.

**Examples:** To make this concrete, let us revisit Figure 3 in Listing 2 where we want a test plan to observe cached responses from the proxy to Dept. Lines 35-38 show the assertion to get a trace (i.e., a sequence of ADUs) that change the state of the data plane such that the last ADU in the abstract traffic trace: (1) is from host H2 (Line 36), (2) corresponds to a cached response (Line 37), and (3) reaches the network port where the monitor is attached to (Line 38). For example, the SE engine might give us a test plan with 5 ADUs: three ADUs between a host in the Dept. and the proxy to establish a TCP connection (the 3-way handshake), a fourth ADU has httpGetObj = httpObjId from the host to the proxy (a cache miss), followed by another ADU with the field httpGetObj set to httpObjId to induce a cached response. Similarly, Listing 4 shows an assertion in Lines 5-6 so that an alarm is triggered at both L-IPS and H-IPS of the example from Figure 2.

### 7.2 Optimizing SE

While SE is orders of magnitude faster than other candidates as the search mechanism, it is still not sufficient for interactive testing: even after a broad sweep of configuration parameters and command line arguments (e.g., max-sym-array-size, max-memory, and optimize) to customize KLEE, it took several hours even for a small topology (§10). To scale to larger topologies, we implement two key optimizations:

- **Minimizing number of symbolic variables:** Making an entire ADU structure (Listing 1) symbolic will force KLEE to find values for every field. To avoid this, Armstrong uses the policy scenario to determine a small subset of ADU fields as symbolic; e.g., when it is testing data plane with a stateful firewall but without a proxy, it makes the HTTP-relevant fields concrete (i.e., non-symbolic) by assigning the don’t care value (represented by -1 in our implementation) to them. As another example, Armstrong sets a client’s TCP port number to a temporary value (as opposed to making the srcPort field symbolic). This value is only used in the model for test planning and the actual client TCP port is chosen by the host at run time (§7.3).

- **Scoping values of symbolic variables:** The TraceSpec already scopes the range of values each ADU can take. Armstrong further narrows this range by using the policy scenario to constrain possible values of symbolic ADU fields. For example, while tcpSYN is an integer ADU field, Armstrong restricts its value to be either 0 or 1 to shrink the search space.

### 7.3 Generating concrete test traffic

The output of SE is a sequence of ADUs ADUSEq\(SE\), and our next goal is to translate it into concrete test packets. Since ADUs are abstract I/O units, we cannot directly inject them into the data plane. Moreover, we cannot simply

```plaintext
Listing 4: Assertion pseudocode for Figure 5 to trigger alarms at both IPSes.
1 // Global state variables
2 int L_IPS_Alarm[noOfHosts]; // alarm per host
3 int H_IPS_Alarm[noOfHosts]; // alarm per host
4 ...
5  assert(!(L_IPS_Alarm[A[i].srcIP]) ||
6  !(H_IPS_Alarm[A[i].srcIP]));
```
do a one-to-one translation between ADUs and raw packets and do a trace replay \[2\], e.g., we need some session semantics for TCP or in an actual HTTP session several parameters will be outside of our control (e.g., chosen by the remote server at the test run time). While we do not claim to have a comprehensive algorithm for translating an arbitrary ADUSeq into concrete test traffic, we use a heuristic approach as follows.

We have created a library using domain knowledge to map a known ADUSeq into a test script. For instance, if we have an ADUSeq consisting of three ADUs for TCP connection establishment and a web request, we map this into a simple wget request with the required parameters (e.g., server IP and object URL) for the request indicated by the ADUSeq. In the most basic case, the script will be a simple IP packet. In our current implementation, we have manually populated this library and currently use 11 such traffic generation primitive functions (e.g., closeTCP, getHTTP, sendIPPacket) that support IP, TCP, UDP, HTTP, and FTP. Automating the task of populating such a trace library is outside the scope of the paper.

Now, given a ADUSeq, we use this library as follows. We partition the ADUSeq based on srcIP-dstIP pairs (i.e., communication end-points) of ADUs; i.e., \( ADUSeq^{SE} = \bigcup_j ADUSeq_j \). Then for each partition \( ADUSeq_j \), we do a longest-specific match (i.e., match on a protocol at the highest possible layer of the network stack) in our test script library, retrieve the corresponding scripts for each subsequence and then concatenate these scripts. We acknowledge this step is heuristic and creating a comprehensive mapping process is outside the scope of this paper.

8 Test Monitoring and Validation

After the test traffic is injected into the data plane, the outcome should be monitored and validated. First, we need to disambiguate true policy violations from those caused by background interference. Second, we need mechanisms to help localize the misbehaving NFs. While a full solution to fault diagnosis and localization is outside the scope of this paper, we discuss the practical heuristics we implement.

Monitoring: Intuitively, if we can monitor the status of the network in conjunction with the test injection, we can check if any of the background or non-test traffic can potentially induce false policy violations. Rather than monitor all traffic (we refer to this as MonitorAll), we can use the intended policy to capture a smaller relevant traffic trace; e.g., if the policy is involves only traffic to/from the proxy, then we can focus on the traffic on the proxy’s port. To further minimize this monitoring overhead, as an initial step we capture relevant traffic only at the switch ports that are connected to the stateful NFs rather than collect traffic traces from all network ports. However, if this provides limited visibility and we need a follow-up trial (see below), then we revert to logging traffic at all ports for the follow-up exercise.

Validation and localization: Next, we describe our current workflow to validate if the test meets our policy intent, and (if the test fails) to help us localize the sources of failure otherwise. The workflow naturally depends on whether the test was a success/failure and whether we observed interfering traffic as shown in Table 1.

Given the specific policy we are testing and the relevant traffic logs, we determine if the network satisfies the intended behavior; e.g., do packets follow the policy-mandated paths? In the easiest case, if the observed path \( Obs \) matches our intended behavior \( Orig \) and we have no interfering traffic, this step is trivial and we declare a success. Similarly, if the two paths match, even if we have potentially interfering traffic, but our monitoring reveals that it does not directly impact the test (e.g., it was targeting other applications or servers), we declare a success.

Clearly, the more interesting case is when we have a test failure; i.e., \( Obs \neq Orig \). If we identify that there was no truly interfering traffic, then there was some potential source of policy violation. Then we identify the largest common path prefix between \( Obs \) and \( Orig \); i.e., the point until which the observed and intended behavior match and to localize the source of failure, we zoom in on the “logical diff” between the paths. However, we might have some logical gaps because of our choice to only monitor the stateful NF-connected ports; e.g., if the proxy response is not observed by the monitoring device, this can be because of a problem on any link or switch between the proxy and the monitoring device. Thus, when we run these follow up tests, we enable MonitorAll to obtain full visibility.

Finally, for the cases where there was indeed some truly interfering traffic, then we cannot have any confidence if the test failed/succeeded even if \( Obs = Orig \). Thus, in this case the only course of action is a fallback procedure to repeat the test but with MonitorAll enabled. In this case, we use an exponential backoff to wait for the interfering flows to die.

9 Implementation

NF models: We wrote C models for switches, ACL devices, stateful firewalls (capable of monitoring TCP connections and blocking based on L3/4 semantics), NATs, L4 load balancers, HTTP/FTP proxies, passive monitoring, and simple intrusion prevention systems (counting failed connection attempts and matching payload signatures). Our models are between 10 (for a switch) to 100 lines (for a proxy cache) of C code. The main loop of network model, utility functions, and header files (e.g., ADU definitions and utility functions) have a total of fewer than 200 LoC. To put these numbers in context, the real-world middleboxes can range from 2K (e.g., Balance [1]) to few 100K (e.g., Squid [16], Snort [15]).
reuse common templates across NFs; e.g., TCP connection sequence used both in firewall model and proxy model.

**Validating NF models:** First, we use a bounded model checker, CMBC [3], on individual NF models and the network model to ensure they do not contain software bugs (e.g., pointer violations). This was a time-consuming but one-time task. Second, we used call graphs visualization [8, 19] based on extensive, manually generated input traffic traces to check that the model behaves as expected.

**Test traffic generation and injection:** We use KLEE with the optimizations discussed earlier to produce the ADU-level test traffic, and then translate it to test scripts that are deployed at the injection points. Test traffic packets are marked by setting a specific (otherwise unused) bit.

**Traffic monitoring and validation:** We currently use offline monitoring via tcpdump (with suitable filters); we plan to integrate more real-time solutions like NetSight [40]. We use OpenFlow [48] to poll/configure switch state.

## 10 Evaluation

In this section, we show that:

1. Armstrong enables close-to-interactive running times even for large topologies (§10.1);
2. Armstrong’s design is critical for scalability (§10.2); and
3. Armstrong successfully helps diagnose a broad spectrum of data plane policy violations (§10.3).

**Testbed and topologies:** To run realistic large-scale experiments with large topologies, we use a testbed of 13 server-grade machines (20-core 2.8GHz servers with 128GB RAM) connected via a combination of direct 1GbE links and a 10GbE Pica8 OpenFlow-enabled switch. On each server, with KVM installed, we run injectors and software NFs as separate VMs, connected via OpenvSwitch software switches. The specific stateful NFs (i.e., middleboxes) are iptables [7] as a NAT and a stateful firewall, Squid [16] as a proxy, Snort [15] as an IPS/IDS, Balance [1] as the load balancer, and PRADS [14] as a passive monitor.

In addition to the example scenarios from §2, we use 8 randomly selected recent topologies from the Internet Topology Zoo [17] with 6–196 nodes. We also use two larger topologies (400 and 600 nodes) by extending these topologies. These serve as switch-level topologies; we extend them with different NFs to enforce policies. As a concrete policy enforcement scheme we implemented a tag-based solution to handle dynamic middleboxes [50]. We reiterate that the design/implementation of this scheme is not the goal of Armstrong; we simply needed some concrete solution.

### 10.1 Scalability of Armstrong

We envision operators using Armstrong in an interactive fashion; i.e., the time for test generation should be within 1-2 minutes even for large networks with hundreds of switches and middleboxes.

**Impact of topology size:** We fix the policy size (i.e., the length the chain of stateful NFs in the policy) to 3, including a NAT, followed by a proxy, followed by a stateful firewall. The firewall is expected to block access from a fixed subset of origin hosts to certain web content. To each switch-level topology, we add a number of middleboxes (0.5 × #switches) and connect each middlebox to a randomly selected switch with at most one middlebox connected to each switch. There is also one host connected to each switch that will be used as the end point of policies. The smallest topology with 6 switches (Heanet) has one instance of the policy chain (i.e., a NAT, a proxy, and a firewall); we linearly increase the number of policy chains to test as a function of topology size.

Figure 9 shows the average test traffic generation latency. (Values are close to the average we do not show error bars). In the largest topology with 600 switches and 300 middleboxes (i.e., 100 policy chain instances), the traffic generation latency of Armstrong is 113 seconds. To put this in context, we also show the traffic generation time of a strawman solution of using CMBC [3] model checker on our data plane model. Even on a tiny 9 node topology with 6 switches and 3 middleboxes this took 25 hours; i.e., Armstrong on 90× larger topology is at least five orders of faster than the status quo. Note that this result considers Armstrong running sequentially; we can trivially parallelize Armstrong across the different policy scenarios.

**Impact of policy complexity:** Next we consider the effect of policy complexity measured by the number of middleboxes present in the policy. We fix the topology to have 92 middleboxes (Heanet). To stress test Armstrong, we generate synthetic longer chains in which the intended action of each NF on the chain depends on some contextual information from the previous NF. Figure 10 shows that even in case of the longest policy chain with 15 middleboxes, Armstrong takes only 84 seconds. Again to put the number in context we show the strawman.

![Figure 9: Test generation latency vs. topology size.](image)

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**Break-down of test traffic generation latency:** Recall from §7 that test generation in Armstrong has two stages. We find that translating abstract test traffic into concrete test

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![Figure 10: Test latency vs. policy chain length.](image)
traffic composes between 4–6% of the entire latency to generate the test traffic; this is the case across different topology sizes and policy sizes (i.e., policy chain lengths) (not shown).

**End-to-end overhead:** After Armstrong generates test traffic, it injects the test traffic, monitors it, and determines the result. The actual test on the wire lasts ≤ 3 seconds in our experiments with 600 switches and 300 middleboxes. However, we monitor the network for a longer 10-second window to capture possibly relevant traffic events. On our largest topology with 600 nodes this validation analysis took only 87 seconds (not shown).

### 10.2 Armstrong design choices

Next, we do a component-wise analysis to demonstrate the effect of our key design choices and optimizations.

**Code vs. models:** Running KLEE on smallest NF codebase of around 2000 LOC (i.e., balance [1]) took about 20 hours. In very small experiment with policy chain of length 2 involving only one switch directly connected to a client, a server, a load balancer, and a monitor [14], traffic generation time took 57 hours (not shown).

**ADU vs. packet:** First, to see how aggregating a sequence of packets as an ADU helps with scalability, we vary file size in an HTTP request and response scenario. Then, we use Armstrong to generate test traffic to test the proxy-monitor policy (Figure 3) in terms of ADUs vs. raw MTU-sized packets. Figure 11 shows that on the topology with 600 switches and 300 middleboxes test traffic generation latency increases vs. the size of the response. Because the number of test packets is dominated by the number of object retrieval packets, aggregating all file retrieval packets as one ADU significantly cuts the latency of the test traffic generation. (The results, not shown, are consistent across topologies as well as using FTP instead of HTTP.)

![Figure 11: Effect of using ADU vs. packet for various request sizes.](image)

**SE vs. model checking:** Our results already showed dramatic gains of Armstrong w.r.t. model checking on the raw code. One natural question is if model checking could have benefited from the other Armstrong optimizations. To this end, we evaluated the performance of an optimized CMBC-based model checking solution with Armstrong-specific optimizations such as FSM Ensembles, ADUs, and other scoping and variable reduction optimizations (§7). This optimized version was indeed significantly faster than before but it was still two orders of magnitude slower than Armstrong (not shown). This suggests that while our abstractions are independently useful for other network verification efforts using model checking, these mechanisms are not directly suitable for the interactive testing time-scales we envision in Armstrong.

**Impact of SE optimizations:** We examine the effect of the SE-specific optimizations (§7) in Figure 12. To put our numbers in context, using KLEE without any optimizations on a network of six switches and one policy chain with three middleboxes took ≥ 19 hours. We see that minimizing the number of symbolic variables reduces the test generation latency by three orders of magnitude and scoping the values yields a further ≥ 9× reduction.

### 10.3 End-to-end use cases

Next we also demonstrate the effectiveness of Armstrong in finding policy violations.

**Diagnosing induced enforcement bugs:** We used a “red team–blue team” to evaluate the end-to-end utility of Armstrong in debugging policy violations. Here, the red team (Student 1) informs of the blue team (Student 2) of policies for each network, and then secretly picks one of the intended behaviors (at random) and creates a failure mode that causes the network to violate this policy; e.g., misconfiguring the L-IPS count threshold or disabling some control module. The blue team uses Armstrong to (a) identify that a violation occurred and (b) localize the source of the policy violation. We also repeated these experiments reversing student roles; but do not show these results for brevity.

Table 2 highlights the results for a subset of these scenarios and also shows the specific traces that Armstrong generated. Three of the scenarios use the motivating examples from §3. In the last scenario (Conn. limit.), two hosts are connected to a server through an authentication server to prevent brute-force password guessing attacks. The authentication server is expected to halt a host’s access after 3 consecutive failed log in attempts. In all scenarios the blue-team successfully localized the failure (i.e., which NF, switch, or link is the root cause) within 10 seconds. Note that these bugs could not be exposed with existing debugging tools such as ATPG [63], ping, or traceroute [11].

![Figure 12: Improvements due to SE optimizations.](image)

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[1] They can detect link/switch failure being down but cannot capture subtle bugs w.r.t. stateful/context-dependent behaviors.
Loops and reachability: Armstrong can also help in diagnosis reachability problems as well. It is worth nothing that while checking such properties in stateless is easy [43], this does not extend to stateful data planes. We extended Armstrong to support reachability properties via new use of assertions. For instance, to detect loops we add assertions of the form: assert(seen[ADU.id][port]<K), where ADU is a symbolic ADU, port is a switch port, and K reflects a simplified definition of a loop that the same ADU is observed at the same port ≥ K times. Similarly, to check if some traffic can reach PortB from PortA in the network, we initialize a ADU with the port field to be PortA and use an assertion of the form assert(ADU.port != PortB). Using this technique we were able to detect synthetically induced switch forwarding loops in stateful data planes (not shown).

11 Related Work

Network verification: There is a rich literature on static reachability checking [34, 42, 43, 47, 61, 62]. At a high level, these focus on simple properties (e.g., black holes, loops) and do not tackle networks with complex middleboxes. NICEcombines model checking and symbolic execution to find bugs in control plane software [32]. Armstrong is complementary in that it generates test cases for data plane behaviors. Similarly, SOFT generates tests to check switch implementations against a specification [45]. Again, this cannot be extended to middleboxes.

Test packet generation: The work closest in spirit to Armstrong is ATPG [63], which builds on HSA to generate test packets to test reachability. As we discussed earlier [2], it cannot be applied to our scenarios. First, middlebox behaviors are not “stateless transfer functions”, which is critical for the scalability of ATPG. Second, the behaviors we want to test require us to look beyond single-packet test cases.

Programming languages: Other work attempts to generate “correct-by-construction” programs [25, 26, 38]. Currently their semantics do not currently capture stateful data planes and context-dependent behaviors. That said, our work in Armstrong is complementary to such enforcement mechanisms; e.g., active testing may be our only option to check if the network with proprietary NMs behaves as intended.

Network debugging: There is a rich literature for fault localization in networks and systems (e.g., [37, 51, 56, 57]). These algorithms can be used in the inference engine of Armstrong. Since this is not the primary focus of our work, we use simpler heuristics.

Modeling middleboxes: Joseph and Stoica formalized middlebox forwarding behaviors but don’t model stateful behaviors [41]. The only work that models stateful behaviors are FlowTest [35], Symnet [59], and work by Panda et al [52]. FlowTest’s high-level models are not composable and the AI planning approaches do not scale beyond 4-5 node networks. Symnet [59] uses models written in Haskell to capture NAT semantics similar to our example; based on published work we do not have details on their models, verification procedures, or scalability. The work of Panda et al., is different from Armstrong both in terms of goals (reachability and isolation) and techniques (model checking).

Simulation and shadow configurations: Simulation [12], emulation [5, 10], and shadow configurations [24] are common methods to model/test networks. Armstrong is orthogonal in that it focuses on generating test scenarios. While our current focus is on active testing, Armstrong’s applies to these platforms as well. We also posit that our techniques can be used to validate these efforts.

12 Conclusions

Armstrong tackles a key missing piece of existing network verification efforts—context-dependent policies and stateful data planes introduce fundamental expressiveness and scalability challenges for existing abstractions and exploration mechanisms. We make three key contributions to address these challenges: (1) a novel ADU abstraction for modeling network I/O behavior; (2) tractable modeling of NMs as FSM ensembles; and (3) an optimized test workflow using symbolic execution. We demonstrate that Armstrong can handle complex policies over large networks with hundreds of middleboxes within 1-2 minutes. In doing so we take the “CAD for networks” vision one step closer to reality.
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