

Performance Prediction of On-NIC Network Functions with Multi-Resource Contention and Traffic Awareness

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Abstract

Network function (NF) offloading on SmartNICs has been widely used in modern data centers, offering benefits in host resource saving and programmability. Co-running NFs on the same SmartNICs can cause performance interference due to contention of onboard resources. To meet performance SLAs while ensuring efficient resource management, operators need mechanisms to predict NF performance under such contention. However, existing solutions lack SmartNIC-specific knowledge and exhibit limited traffic awareness, leading to poor accuracy for on-NIC NFs.

This paper proposes Yala, a novel performance predictive system for on-NIC NFs. Yala builds upon the key observation that co-located NFs contend for multiple resources, including onboard accelerators and the memory subsystem. It also facilitates traffic awareness according to the behaviors of individual resources to maintain accuracy as the external traffic attributes vary. Evaluation using BlueField-2 SmartNICs shows that Yala improves the prediction accuracy by 78.8% and reduces SLA violations by 92.2% compared to state-of-the-art approaches, and enables new practical usecases.

1 Introduction

SmartNICs have been prevalent in modern data centers to deploy diverse network functions (NF) due to their benefits in programmability and host resource saving [37, 42, 44, 45, 47, 55, 57, 59, 65]. They typically integrate heterogeneous onboard resources, such as SoC cores and domain-specific hardware accelerators, to cater to various NF demands. Moreover, vendors are developing increasingly resourceful NICs to meet evolving offloading needs [9, 12, 62]. To fully leverage these resources, it is common practice to co-locate multiple NFs on the same NIC [36, 42, 47, 60].

Unfortunately, sharing SmartNIC resources among co-located NFs may lead to contention and performance degradation, posing challenges in maintaining the SLAs. One potential solution is to implement stringent resource isolation mechanisms on SmartNICs. Yet, previous work on this front

Network Function	Accelerator	T	Framework
FlowStats [48, 55]	None	✓	Click
IPRouter [48, 55]	None	✗	Click
IPTunnel [34]	None	✓	Click
NAT [40, 47, 55]	None	✓	Click
FlowMonitor [47, 53]	Regex	✓	Click
NIDS [47, 48]	Regex	✓	Click
IPComp Gateway [13, 61]	Regex, compression	✓	Click
ACL [18, 40]	None	✗	DPDK
FlowClassifier [18, 68]	None	✓	DPDK
FlowTracker [3]	None	✓	DOCA
PacketFilter [3]	Regex	✓	DOCA

Table 1. Typical NFs and accelerators they require from SmartNICs. Common resources (CPU, memory, and NIC subsystems) are not shown. T means that the NF performance heavily depends on the traffic attributes. The regex-based NFs use the same rule set from [5]. The last column indicates the programming framework we use to implement each NF.

requires specific NIC hardware architecture support and substantial rewriting of NF programs to accommodate new isolation abstractions [36, 39], thus limiting their practical deployment. Consequently, developers still need extensive hand-tuning to ensure simultaneous SLA fulfillment for co-located NFs, which is time-consuming and error-prone [36, 41, 47].

Ideally, if operators can predict the performance drop an NF will suffer before actually co-running it with other NFs on the same NIC, they can make better resource management decisions on existing infrastructure and NF implementations. Concretely, SmartNIC platforms [40, 42, 47, 60] and SmartNIC-assisted clouds [2, 16, 29] can maximize NF colocations in SmartNIC offloading while minimizing SLA violations, which correspond to lower total cost of ownership (TCO) for providers and better experience for tenants, and enjoy faster diagnosis and reasoning of on-NIC NF performance compared to slow manual analysis [37, 55]. To achieve these, we need a systematic *on-NIC* NF performance prediction framework, which entails two new challenges.

First, on-NIC NFs often utilize diverse onboard resources including memory and various hardware accelerators, making it common that contentions occur across heterogeneous resources. Prior work on NF performance prediction has

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primarily focused on memory subsystem contention as the sole source of performance interference for on-server NFs [33, 48, 50]. We showcase that the state-of-the-art SLOMO [48] encounters high prediction errors when co-locating NFs contend for both memory and regex accelerator on a BlueField-2 SmartNIC, with $\sim 20\%$ in the median and $\sim 60\%$ in the worst case (§2.2.1). The community lacks a clear understanding of (1) the impact of contention on individual domain-specific accelerators and (2) the overall effect of multi-resource contention on performance.

Second, NF performance is heavily influenced by traffic attributes such as flow counts and payload features, which change dynamically for each NF. Current frameworks often either assume fixed traffic attributes [37, 55], or can only deal with a limited range of variations in these attributes (e.g., 20% in flow counts in [48]).

In this paper, we propose **Yala**, a new performance prediction framework that explicitly considers multi-resource contention and dynamic traffic attributes. Yala conducts offline profiling of on-NIC NFs to collect their performance under diverse synthetic contention levels and traffic attributes. Leveraging these profiles, Yala trains a contention- and traffic-aware model for each NF, which is then used to predict the NF’s performance before its deployment, facilitating placement and other management decisions. We build Yala for SoC SmartNICs due to their ease of programmability (e.g., DPDK and Click support), and tackle the above technical challenges by leveraging critical characteristics of on-NIC NFs.

Multi-resource contention modeling. Yala’s key idea here is to independently model individual resource contention and integrate these per-resource models together. We identify hardware accelerators and memory subsystems as primary sources of contention for on-NIC NFs. For accelerators, we find that it is a common design for NFs to interact with them through their own queues which are coordinated by round-robin scheduling. This inspires us to take a white-box approach and propose a queueing-based contention model. Memory subsystem contention can be modeled using a black-box ensemble-based ML model following existing work [48]. Then, to capture the end-to-end effect of each resource, we introduce *execution-pattern-based composition*. This makes intuitive sense because how each resource and its contention affects the overall performance critically depends on whether NF runs as a pipeline or in a run-to-completion fashion.

Traffic-aware modeling. On top of multi-resource contention, Yala employs *traffic-aware augmentation* to integrate knowledge of traffic attributes into per-resource models. Generally speaking, this can be done by feeding *traffic attributes*, e.g., flow count and packet size, as additional features to per-resource models. Specifically, for accelerators, we can leverage the white-box nature of the queueing-based model and represent key model parameters as a function of traffic attributes; for memory subsystem which has a blackbox

model, we simply fuse traffic attributes with performance counters as features to extend the model. In addition, to curb the high profiling cost caused by the introduction of traffic attributes especially for black-box memory models, Yala adopts *adaptive profiling* to prune attribute dimensions and enforce targeted sampling at performance-critical ranges of the attributes.

We implement Yala in C and Python, leveraging typical offline profiling tools [19, 20, 24, 26] and sklearn [25], and evaluate it on 9 common NFs using BlueField-2 SmartNIC. Our code is open source anonymously at [28]. Our testbed evaluation shows that Yala achieves accurate NF throughput predictions under multi-resource contention and varying traffic attributes, with an average error of 3.7% across NFs which corresponds to 78.8% improvements compared to state-of-the-art SLOMO. As new usecases, we also illustrate that in NF placement, Yala can reduce SLA violations by 88.5% and 92.2% compared to greedy approaches [47, 60] and SLOMO, and in performance diagnosis it can deliver higher accuracy in identifying bottlenecks for on-NIC NFs.

2 Background and Motivation

We start by presenting the brief background of network function resource contention on SmartNICs, followed by the unique challenges of developing a contention-aware performance prediction framework.

2.1 Background

SmartNICs have been widely used to offload various network functions (NFs) in modern data centers, mainly for their benefits in host resource saving and energy efficiency [35, 42, 44, 47, 55, 60]. The NFs leverage the on-board domain-specific hardware accelerators to achieve high throughput and low latency [40, 47, 48, 55]. We showcase some typical NFs seen across prior work [40, 47, 48, 55] and the types of resources they need in Table 1. Here Flow Monitor, NIDS, and PacketFilter require the regex accelerator for packet inspection and payload scanning, and IPComp Gateway requires both the regex and compression accelerators.

Contention degrades performance Recently, co-running multiple NFs on the same SmartNIC has become more common to improve utilization [36, 42, 47, 60]. This can lead to performance degradation due to contention for shared resources. To demonstrate this effect, we profile the throughput drop of 9 typical NFs from Table 1 when they co-locate with other NFs. For each target NF, up to three other NFs are randomly selected (from Table 1)¹. Each NF is given two dedicated cores while sharing the memory subsystem and hardware accelerators due to the lack of hardware- or system-level isolation support on current SmartNICs. Traffic profiles for all NFs consisted of 16K flows of 1500B packets, with flow sizes following the uniform distribution (further

¹Some NFs require minimum two cores, while one BlueField-2 has eight cores in total.

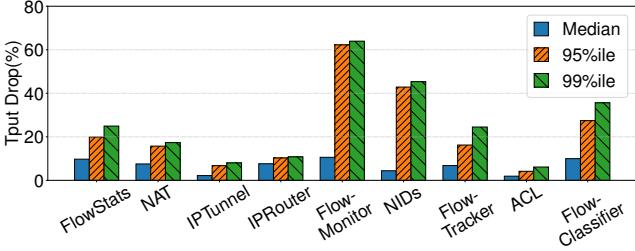


Figure 1. Throughput drop ratios of some NFs from Table 1 under resource contention when co-located with at most 3 other random NFs.

details in §7.1). For NFs processing payloads with regular expressions, we use `exrex` [15] to generate packet payloads. Note the packet arrival rates are set sufficiently high for all NFs to ensure it is not causing throughput drop. We measure the throughput drop ratio against the baseline when the target NF runs alone with two CPU cores, the entire memory and hardware accelerators. Figure 1 depicts the statistics of throughput drop ratios. We can see that when co-running with different (numbers and combinations of) NFs, resource contention can cause 4.2% to 62.2% throughput drop at the 95%ile, and 1.9% to 10.6% at the median.

2.2 Challenges

Modeling and predicting NF performance under resource contention is therefore of paramount importance for many management tasks [33, 37, 48, 50], and some prior work [33, 48, 50] has investigated this problem in network function virtualization where NFs run on commodity servers. An immediate question is, what makes contention-aware performance prediction different in the context of SmartNICs? We now highlight two unique challenges which are not well addressed in past efforts. Note all experiments in this section use the BlueField-2 (BF-2) SmartNIC.

2.2.1 Multi-Resource Contention We've seen that NFs on SmartNIC utilizes multiple heterogeneous onboard resources. Prior work, however, has only considered contention of the memory subsystems [33, 48, 50], missing the contention on other hardware accelerators. Their effectiveness as a result is tainted in the context of SmartNICs.

To empirically substantiate our argument, we co-run Flow-Monitor with up to three competing NFs chosen randomly from Table 1 on one BF-2. The traffic profiles are identical to the one in Figure 1. We use SLOMO [48] as the state-of-the-art memory-based prediction model and develop a new model for the regex accelerator due to lack of existing models (details in §4.1.1).

We first train our single-resource models for FlowMonitor which uses regex accelerator in addition to CPU and memory, and validate their effectiveness under single-resource contention. We build two synthetic NFs, mem-bench and

regex-bench², to assert controllable memory and regex contention, respectively, for generating training data (details in §6). Following SLOMO, we also collect data from our BF-2's performance counters at runtime (e.g., memory read/write rates) as the model input. Absolute percentage error against FlowMonitor's true throughput under single-resource contention is used as the comparing metric. Our models achieve the same <10% average prediction error for memory- and regex-only contention as reported in the SLOMO paper [48].

Then we apply these models directly to the multi-resource contention scenario as said before, where co-locating NFs as a whole contend for both memory and regex accelerator and nothing else. Figure 2(a) shows that prediction error now increases to ~20% in the median and reaches ~60% in the worst case, indicating that only considering one resource is wildly inaccurate.

In addition, NFs exhibit diverse execution patterns when utilizing these resources. For example, one NF may run in a *pipeline* manner for high throughput, while another may wait for the completion of dispatched requests to ensure low average latency (*run-to-completion*) [24, 37]. This makes *composition* of single-resource models, a strawman solution for multi-resource prediction, inaccurate.

To explore this, we analyze two simple composition approaches: (1) sum composition, which adds up the predicted throughput loss from each model [37, 67], and (2) min composition, which uses the maximum predicted throughput loss as the final output [47, 58]. Figure 2(b) presents the results of these two approaches in the same setting as Figure 2(a). We observe that while composition models reduce error, they do not guarantee optimal accuracy across all NFs. For NF1 with run-to-completion, sum composition works better, but its error is significant (~17%) for the pipeline NF2. The key reason is that the resource contention impact on end-to-end throughput varies by NF execution patterns. In pipeline-based NFs, throughput is constrained by the slowest stage on which resource contention causes the most significant performance interference compared. In contrast, for run-to-completion NFs, contention on different resources uniformly impacts the end-to-end throughput.

To quickly recap, NFs on SmartNICs can experience contention across multiple resources, and its impact on performance differs according to the execution patterns. Current systems consider only single-resource contention, which results in substantial prediction inaccuracies.

2.2.2 Traffic Attributes An NF's performance also depends on certain traffic attributes, such as number of flows,

²We build synthetic NFs for three main purposes: 1) collecting training data, 2) exploring insights that support our design choices, and 3) microbenchmarks. For example, regex-bench is purpose-built to have negligible memory subsystem usage but extensive regex accelerator usage, and we rely on it to investigate the contention behavior in regex accelerator (§4.1.1). For evaluations on end-to-end accuracy (§7.2, §7.3, §7.4) and use cases (§7.5), we employ real NFs from Table 1 instead.

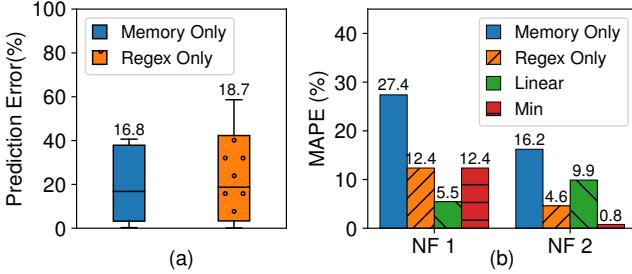


Figure 2. Prediction errors (absolute percentage error) of Flow-Monitor’s throughput using single-resource models. (a) Box and whisker plot of using only the memory-based SLOMO model or a regex-based model (§4.1.1). We show the median error on top of each error box. (b) Mean average percentage error (MAPE) of sum and min composition of single-resource models. NF1 and NF2 adopt run-to-completion and pipeline resource usage pattern respectively.

payload characteristics, etc., in many cases [37, 48, 55]. To see this, we measure FlowStat’s throughput when co-located with mem-bench, and vary mem-bench’s cache access rates (CAR). Figure 3(a) shows that FlowStat’s throughput drops differently in different traffic profiles as mem-bench’s CAR increases, implying that a traffic-agnostic model inevitably leads to high prediction errors when adapting to new traffic profiles.

Figure 3(b) empirically confirms the intuition above for existing work. Here we look at three target NFs: FlowStats, FlowClassifier, and FlowTracker. Each of them is co-located with mem-bench on a single BF-2. We use the same default traffic profiles of 16K flows to train three models for each target NF following SLOMO just as in the experiments before. We then test them under changing traffic attributes by generating 100 distinct traffic profiles with random number of flows up to 500K. It is clear from Figure 3(b) that prediction error increases dramatically when the traffic behavior deviates from the default profiles that the models have seen. Note SLOMO does consider the number of flows in its prediction, but can only handle a small degree of deviation from the training data as we shall detail in §7.1 and §7.4.

3 Yala Overview

The challenges in §2 pose two fundamental questions on accurate performance prediction for on-NIC NFs, which drive Yala’s design:

1. How to model the impact of multi-resource contention on NF performance?
2. How to integrate traffic attributes to contention-aware performance prediction models?

We develop Yala, a framework for accurately predicting on-NIC NF performance with multi-resource contention and varying traffic profiles. To address the first design question, Yala adopts a “divide-and-compose” approach: it builds up individual *per-resource contention models* (§4.1) for both

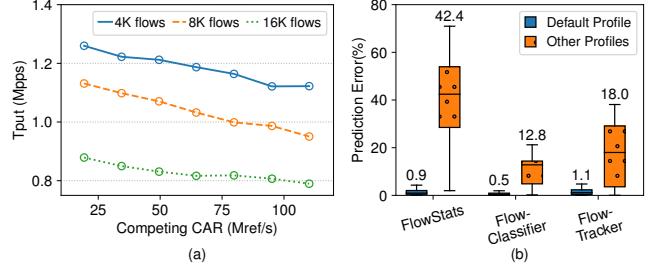


Figure 3. (a) FlowStats’s throughput when the competitor’s cache access rate (CAR) changes in three distinct traffic profiles. CAR is the sum of the cache read and write rates obtained from the hardware performance counters on BlueField-2. (b) Distribution of prediction errors after adapting the model to different traffic profiles. We show the median error on top of each error box.

hardware accelerators and memory subsystem to separately model their impact on throughput, and applies *execution-pattern-based composition* (§4.2) to faithfully capture the end-to-end effect of contention. Then in response to the second design question, Yala introduces *traffic-aware augmentation* (§5.1) techniques to integrate various traffic attributes into per-resource models, and develops an *adaptive profiling* (§5.2) method to balance the soaring profiling costs (due to the extra dimensions of traffic attributes) with model quality. Taken together, during online prediction, Yala takes the contention level of competing NFs and traffic attributes of the target NF as input to the per-resource models and compose the results based on NF’s execution pattern to obtain the final prediction. Consistent with prior work [37, 48, 50], Yala does not require knowledge of or access to NF source code.

4 Multi-Resource Contention Modeling

We now present the design insights and details of Yala’s multi-resource contention modeling. Note we are interested in the NF’s maximum throughput assuming the arrival rate is high enough, which represents the NF’s capability and is consistent with prior work [48, 50, 55].

4.1 Per-Resource Models

An on-NIC NF consumes onboard CPU, memory subsystem (cache and main memory), hardware accelerators, and NIC [36, 37, 41, 55]. For CPU, given common deployment practice [61, 63, 68], we perform core-level isolation for co-located NFs so CPU contention does not happen. Although some prior work has discussed potential isolation issues for NICs on a server [41], we do not encounter this problem as on-NIC NFs leverage powerful hardware-based flow table on SmartNICs [27]. Thus, we focus on contention on hardware accelerators and memory subsystem here, assuming fixed traffic attributes. Notice the per-resource modeling effectively derives the NF’s throughput on one given resource only without accounting for other resources, and may not equal to the overall throughput.

4.1.1 Hardware Accelerators At first glance, modeling hardware accelerator contention seems not much different from existing design for memory contention [48, 50]. That is, one can use an accelerator’s performance counters to quantify NF’s contention level as the input, and employ an ML model to predict throughput. This is infeasible, however, because current SmartNIC accelerators do not expose fine-grained performance counters [8, 10, 20, 23, 45]. We thus propose a general *queue-based* white-box approach for hardware accelerators.

Contention behavior in hardware accelerators. We start by analyzing the accelerator’s contention behavior which our modeling is based upon. Without loss of generality, we use the widely-used regex accelerator [3, 10, 24] as the target of discussion hereafter.

In practice, NFs utilize onboard accelerators via the corresponding queue systems [3, 4]. For example, an NF establishes request queues and enqueues/dequeues operations to/from a regex accelerator [3, 4, 24]. This queue-based interface unifies the interaction with specialized accelerators and applies to many SmartNICs [8, 9, 12] and beyond [11, 38]. Understanding the queue system behavior is then crucial for modeling accelerator contention.

Setup. We write a synthetic Click NF called regex-NF that utilizes regex accelerator to scan packet payloads. regex-NF’s packet arrival rate is high enough to ensure maximum throughput, and it is tested with different match-to-byte ratios (MTBR).³ To vary contention level, we adjust the co-running regex-bench’s arrival rate.

Observation. We depict the throughput results in Figure 4 and make two interesting observations. *O1:* First, regex-NF shows *linear* throughput drop as the contention from regex-bench rises. *O2:* Second, regex-NF finally reaches the equilibrium throughput without further dropping. The equilibrium point clearly varies with regex-bench’s MTBR.

These two observations are very familiar to us as they point to the canonical round-robin (RR) queuing discipline widely used in practice. Indeed, we confirm from [7] that our regex accelerator driver’s implementation adopts RR for queue-level fairness. With one queue per each NF which is the setup in our experiment, as regex-bench’s request arrival rate increases, regex-NF’s requests have proportionally less access to the accelerator, resulting in the linear throughput decline. When contention is high enough that regex-bench’s queue is always non-empty when the RR scheduler turns to it, throughput of regex-NF stops dropping since its average sojourn time (sum of queuing and processing times) stops increasing [52]. As they have the same numbers of queues, their equilibrium throughput is the same as seen in Figure 4.

³Match-to-byte-ratio (MTBR) refers to how many matches against a regex ruleset is contained in each byte of the payload. A higher MTBR reflects more regex matches with in each unit of packet payload and longer processing time for a packet (§7.1).

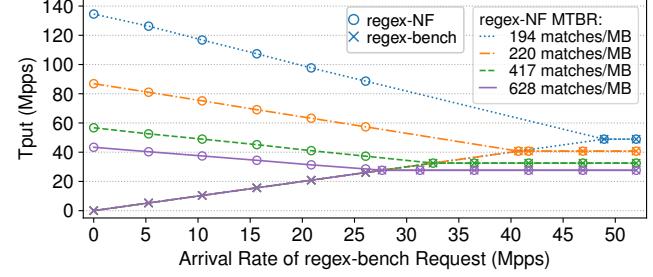


Figure 4. Throughput of co-running synthetic pattern-matching “regex-NF” and regex-bench as a function of arrival rate of regex-bench. In each setting, regex-NF and regex-bench reach an equilibrium throughput, e.g., with MTBR of 194 matches/MB for regex-NF, they both obtain 48.9 Mpps at equilibrium.

Our approach. Motivated by the above analysis, the regex accelerator contention can be modeled by RR over multiple request queues with one service node (*i.e.*, the accelerator). Suppose we have N NFs sharing an accelerator, and each NF_j has n_j request queues. At equilibrium, the average sojourn time t of requests from each queue is [52]: $t = \sum_{j=1}^N n_j t_j$, where t_j represents NF_j ’s average request processing time. For a target NF_i , its throughput T_i can be represented as the sum of throughput of all its queues, *i.e.*,

$$T_i = \frac{n_i}{t} = \frac{n_i}{\sum_{j=1}^N n_j t_j} = \frac{n_i}{\sum_{j=1}^N \frac{n_j^2}{T_{j,solo}}}, \quad (1)$$

where $T_{j,solo}$ represents its regex processing throughput (in pps) when NF_j runs solo. Clearly when $n_i = n$ for all NFs, they have the same (equilibrium) throughput T_i .

Now to use Equation (1) for a new NF, we need to infer n_j and $T_{j,solo}$ without any knowledge of the NF. Recall $T_{j,solo}$ is throughput on the regex accelerator only, which may or may not equal to end-to-end throughput if the NF is bottlenecked on other resources or follows run-to-completion. So to estimate them accurately, we again co-run the NF with regex-bench and set regex-bench’s request processing time and match rate to be high enough to ensure that at equilibrium, the NF spends most of its time on regex. We then collect two sets of equilibrium throughput data to solve for n_j and $T_{j,solo}$ since regex-bench’s parameters are known.

We verify Equation (1) with empirical results of various regex-based NFs, which show that our approach is accurate with 1.3% error on average.

Other accelerators. Our approach here directly applies to other hardware accelerators, *e.g.*, compression and crypto accelerator, which also uses round-robin based queues[13, 22].

4.1.2 Memory Subsystem Memory subsystem contention has been studied in existing work [33, 48, 50] which finds that the contention-induced throughput drop can be

modeled as a *piece-wise linear* function of performance counters. Thus we follow SLOMO’s gradient boosting regression (GBR) method which is state-of-the-art, using 7 performance counters as input features. Note that we overcome the fixed-traffic limitation of GBR by integrating traffic attributes to it in §5.

4.2 Execution-Pattern-Based Composition

We now discuss how to composite the per-resource models for deriving end-to-end throughput.

Observations. We analyze two typical execution patterns of NFs: *pipeline* and *run-to-completion* [24, 37]. In the following discussion, we define a *stage* as a processing block that will only utilize one resource type. Considering a packet received by a pipeline NF, or p-NF, and a run-to-completion NF, or r-NF: for p-NF, the packet waits at the first stage until its predecessor *enters* the second stage; for r-NF, the packet waits until the predecessor *leaves* the last stage.

Figure 5 presents the throughput of a synthetic p-NF (top) and r-NF (bottom) under different levels of memory and regex accelerator contention. We observe that: *O1*: the p-NF’s throughput stays unchanged when memory contention is low and regex contention is high. For example, the throughput stays at ~400 Kpps when competing cache access rate (CAR) is less than ~100 Mref/s and competing match rate (product of throughput and MTBR) is 2500 Kmaches/s. This is because the throughput of a pipeline equals that of its slowest stage – regex matching in this case, making it insensitive to memory subsystem contention. *O2*: Second, for the r-NF, we observe that throughput drop is a *monotonically decreasing* function of both competing CAR and regex match rate, indicating that throughput drop is always caused by the compounded contention.

Our approach. The main goal here is to derive a composing function that takes in execution pattern and per-resource throughput drop $\Delta T_k, 1 \leq k \leq r$ (given by per-resource models) as input, and produces the end-to-end throughput drop caused by contention in r resources.

Pipeline: Based on *O1*, end-to-end throughput (denoted as T) of a p-NF can be calculated as:

$$T = T_{\text{solo}} - \max(\Delta T_1, \dots, \Delta T_r), \quad (2)$$

where T_{solo} is the NF’s throughput when running solo.

Run-to-completion: Based on *O2*, we denote the processing time of a packet in each resource without contention as t_k (also the sojourn time), where $1 \leq k \leq r$. Due to multi-resource contention, the sojourn time of a packet in each resource grows by Δt_k as a result of throughput drop ΔT_k . Therefore, the throughput of the r-NF can be represented as:

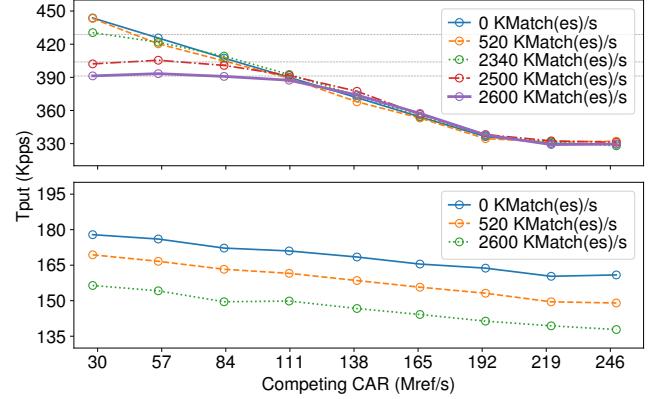


Figure 5. Throughput of two synthetic Click NFs that use pipeline (top) and run-to-completion (bottom) as a function of competing CAR in memory subsystem and match rate in regex accelerator.

$$\begin{aligned} T &= \frac{1}{\sum_{k=1}^r (t_k + \Delta t_k)} = \frac{1}{\sum_{j=1}^r \left(t_j + \Delta t_j + \sum_{k=1, k \neq j}^r t_k \right)} - \sum_{j=1}^r \sum_{k=1, k \neq j}^r t_k \\ &= \frac{1}{\sum_{j=1}^r \frac{1}{T_{\text{solo}} - \Delta T_j} - \frac{r-1}{T_{\text{solo}}}}. \end{aligned} \quad (3)$$

Detecting execution pattern. Without source code access, we resort to a simple testing procedure to detect an NF’s execution pattern. We co-run the NF with our benchmark NFs, and see if Equation 2 or 3 fits its throughput drop better. One may also observe the NF’s throughput curve similar to Figure 5 to empirically determine if it is a p- or r-NF.

5 Traffic-Aware Prediction

Our discussion so far has been limited to fixed NF traffic profiles. Now we discuss how to integrate traffic attributes into our models.

5.1 Traffic-Aware Augmentation

It is obvious that we need to augment the per-resource model with knowledge of traffic attributes, while execution-pattern-based composition is not affected. To do this, we select three common traffic attributes that impact NF performance based on our experiment results and previous studies [37, 48]: number of flows or flow count, packet size, and match-to-byte-ratio (MTBR) of a packet. We denote a traffic profile of 16K flows, 1500B packets and 600 matches/MB payload using a vector (16000, 1500, 600).

5.1.1 Hardware Accelerators We again start with hardware accelerators, specifically the regex accelerator, as a concrete example.

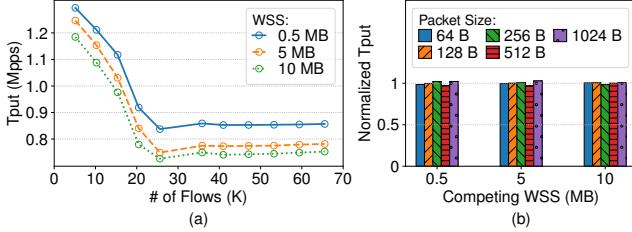


Figure 6. Throughput of FlowStats as a function of traffic attributes. (a) The packet size is 1500 B. (b) The number of flows is 16 K.

Our approach. A regex-utilizing NF is naturally sensitive to the MTBR of packet payload [24].⁴ It directly impacts the average processing time of the regex requests.

Following notations from Equation 1, the average request processing time of NF_j for a given ruleset can be expressed as: $t_j = \frac{1}{T_{j,\text{soho}}} = t_{j,0} + a_j m_j$, where $t_{j,0}$ and a_j are constants, and m_j is the MTBR. This equation builds on the intuition that that request processing time grows linearly with number of matches in a packet, as each match induces a constant amount of extra processing time on average on top of the base processing time. Plugging into Equation 1, the traffic-aware throughput model of regex accelerator is:

$$T_i = \frac{n_i}{\sum_{j=1}^N n_j^2 (t_{j,0} + a_j m_j)}. \quad (4)$$

The parameters $t_{j,0}, a_j$ can be easily obtained from linear regression using data from co-running the NF with regex-bench under different MTBRs.

Other accelerators. Per-resource models for other accelerators can be augmented in a similar two-step approach: (1) analyzing what accelerator-specific traffic attributes affect the NF; (2) representing the average processing time as a function of these accelerator-specific traffic attributes.

5.1.2 Memory Subsystem We co-run FlowStats with mem-bench with different numbers of flows (other traffic attributes stay the same). We adjust the working set size of mem-bench and keep other metrics (*i.e.*, CAR and memory access rate) fixed. Figure 6(a) reveals that FlowStats experiences significant throughput drop with increasing flow count. More interestingly, the throughput curve is also a *piece-wise* function of the number of flows, which is similar to memory contention modeling as mentioned in §4.1.2 (we shall explain this in §5.2 later). Thus, we take a straight-forward approach to add traffic attribute knowledge as extra features to the blackbox GBR model of memory subsystem, by appending the traffic attributes vector to the original input vector of performance counters.

5.2 Adaptive Profiling

Being traffic-aware brings a new and critical issue: training a traffic-aware model now needs more data due to the higher

Algorithm 1 Adaptive profiling.

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1:  $nf$ : The target NF to be profiled
2:  $C$ : The list of performance counters
3:  $\mathcal{F}$ : The list of traffic attributes
4:  $q, \epsilon_0, \epsilon_1, m$  are hyperparameters
5: function ADAPTIVE_PROFILE( $nf, C, \mathcal{F}$ )
6:    $n \leftarrow 0$ 
7:   for  $f$  in  $\mathcal{F}$  do
8:      $T_{min} \leftarrow PROFILE\_ONE(nf, 0, f_{min}, n)$ 
9:      $T_{max} \leftarrow PROFILE\_ONE(nf, 0, f_{max}, n)$   $\triangleright "0"$  represents
       no contention.  $f_{min}$  and  $f_{max}$  represent the lowest and highest
       possible value of  $f$  respectively.
10:    if  $|T_{max} - T_{min}| < \epsilon_0$  then
11:       $\mathcal{F} \leftarrow \mathcal{F} - \{f\}$   $\triangleright$  Prune the traffic attribute.
12:    else RANGE_PROFILE( $nf, \mathcal{F}_{min}, \mathcal{F}_{max}, n$ )  $\triangleright \mathcal{F}_{min}$  and  $\mathcal{F}_{max}$ 
       mean all traffic attributes take the lowest and highest possible
       value respectively.
13:    return
14: function RANGE_PROFILE( $nf, \mathcal{F}_{min}, \mathcal{F}_{max}, n$ )
15:    $T_{min} \leftarrow PROFILE\_ONE(nf, 0, \mathcal{F}_{min}, n)$ 
16:    $T_{max} \leftarrow PROFILE\_ONE(nf, 0, \mathcal{F}_{max}, n)$ 
17:   if  $n \geq q$  then  $\triangleright$  We reach profiling quota.
18:     return
19:   if  $|T_{max} - T_{min}| \geq \epsilon_1$  then
20:      $\mathcal{F}_{mid} \leftarrow \frac{\mathcal{F}_{max} + \mathcal{F}_{min}}{2}$ 
21:     for  $_m$  in  $m$  do
22:        $C_r \leftarrow RANDOM()$   $\triangleright$  Choose a random contention
          level to apply on target NF.
23:       PROFILE_ONE( $nf, C_r, \mathcal{F}_{mid}, n$ )
24:     RANGE_PROFILE( $nf, \mathcal{F}_{mid}, \mathcal{F}_{max}, n$ )
25:     RANGE_PROFILE( $nf, \mathcal{F}_{min}, \mathcal{F}_{mid}, n$ )
26:   return

```

dimensionality of the input vector compared to a fixed-traffic model. This is especially true for the black-box model for memory subsystem, which already has a high-dimensional input vector. A naive solution is to repeat the collection process for each unique traffic profile (*a.k.a.* full profiling), which obviously leads to massive exponentially-growing profiling overheads. Although random sampling based profiling [48, 50] can effectively reduce overhead, it may cause high prediction error due to inadequate coverage of the data space. The trade-off between profiling cost and model accuracy motivates us to design an optimized profiling method for Yala.

Observations. Our design has roots on two key observations. First, an NF’s performance is only dependent on a few traffic attributes. For example, FlowStats is only sensitive to number of flows as in Figure 6(a), but not packet size as in Figure 6(b), since it only processes packet header.

Second, for a given traffic attribute, it causes significant performance drops only in a limited range of values; performance shows little changes in other ranges. Still using FlowStats, when the competing WSS is 10MB, its throughput loses ~30% for [1, 20K] flows, but remains almost unchanged

⁴Number of queues is fixed during NF’s life cycle per its configuration.

for $[40, 60K]$ flows as in Figure 6(a). This is because FlowStats’s hash table grows as a result of growing flow count. Before it fully occupies the last level cache (LLC), increasing the hash table size leads to higher cache miss ratio, which slows down read/write operations and thus throughput. After the LLC is saturated, cache miss ratio stays at a fixed level, causing NFs to exhibit constant throughput. These characteristics also hold in general across NFs as we empirically observe for other NFs in Table 1. This is because generally, (1) NFs typically process either packet headers or payloads, which only depends on several traffic attributes; and (2) traffic attributes usually affect performance by changing the size of key data structures in the NF processing logic, e.g., the mapping table in NAT [34, 48, 50], which exhibits the same LLC effect as explained just now.

Our approach. Our key idea is to prune irrelevant traffic attribute dimensions, and conduct more sampling for relevant traffic attributes within the critical value ranges where NF performance has salient changes. We propose a two-step adaptive profiling algorithm that balances between model accuracy and profiling cost.

As shown in Algorithm 1, we first test whether NF performance is sensitive to a traffic attribute or not. Suppose the possible range of an attribute f is $[f_{min}, f_{max}]$. We profile the NF’s solo throughput with f set to f_{min} and f_{max} respectively while other attributes remain default (lines 8–9). Then we compare the throughput difference to determine if f should be added in our model. Note that the function `PROFILE_ONE()` collects throughput data under a specified configuration (contention level and traffic attribute), and increments the total number of collected samples by one if the configuration has not been profiled. After pruning the attribute list, we carry out a binary search to adaptively collect profiling data. For each call to `RANGE_PROFILE()`, we consider the difference between solo throughputs on traffic attribute boundaries. If their difference exceeds a certain threshold, we collect m data points at the center of current traffic attribute region (lines 18–22). Then the traffic attribute region is split in half, which will serve as the new region for the recursive call of `RANGE_PROFILE()`.

6 Implementation

We implement Yala with ~ 1600 LoCs in C and Python. Yala employs `perf-tools` [20] and a working set size estimation tool [1] to collect performance counters. Yala uses `sklearn` [25] to construct machine learning models used in per-resource models. Our code is open source anonymously at [28].

Synthetic benchmarking NFs. We implement three synthetic NFs called mem-bench, regex-bench and compression-bench (~ 8300 LoCs in C with DPDK support) based on open-source benchmark tools [4, 19, 24, 26] to apply configurable levels of contention on memory subsystem, regex, and compression accelerators, respectively.

Network functions. We implement common on-NIC NFs with ~ 3600 LoCs in C and Click using frameworks including Click 2.1 [34], DPDK 20.11.6 [18], and DOCA 1.5-LTS [3]. Our BF-2 enables hardware flow table offloading for NFs.

7 Evaluation

We present our evaluation of Yala now. The highlights are:

- (1) **Accuracy:** Yala achieves an average prediction error of 3.7% end-to-end, with 78.8% error reduction compared to state-of-the-art across NFs (§7.2). Microbenchmarks further show that Yala’s design choices on multi-resource contentions and changing traffic attributes are effective (§7.3, §7.4).
- (2) **Usecases:** To see how Yala can be beneficial in practice, we show two concrete usecases where it (1) facilitates resource-efficient placement decisions in NF scheduling, reducing NF SLA violations by 88.5% and 92.2% compared to the classical greedy-based approaches and SLOMO, and (2) enables fast performance diagnosis for NFs under contention with 100% accuracy (§7.5).
- (3) **Overhead:** Yala’s offline adaptive profiling reduces profiling cost while maintaining high model accuracy (§7.6).

7.1 Methodology

We employ NVIDIA BlueField-2 (BF-2) to evaluate Yala. A BF-2 SmartNIC has 8 ARMv8 A72 cores at 2.5GHz, 6MB L3 cache, 16GB DDR4 DRAM, dual ConnectX-6 100GbE ports, and hardware accelerators for regex and compression. The NF traffic is generated from a client machine with an AMD EPYC-7542 CPU with 32 cores at 2.9GHz and a ConnectX-6 100GbE NIC. Both the BF-2 server and client machine are connected to a Mellanox SN2700 switch.

Traffic profiles. We employ DPDK-Pktgen [21] to create various traffic profiles with different attributes, i.e., number of flows and packet sizes. In addition, we generate packet payloads using exrex [15] with diverse MTBR of conducting regular expression matches for NFs using regex accelerator. The rule sets are from [5].

Baseline. SLOMO [48] serves as our baseline. For each NF, we train a model using SLOMO’s gradient boost regression under the default traffic profile, which has 16K flows, 1500B packet size, and the MTBR at 600 matches/MB. If in testing the traffic profile deviates from default, we employ SLOMO’s sensitivity extrapolation⁵ to adapt the model (Section 6 in [48]). We validate that our models achieve the same level of prediction error as in [48].

Metrics. We report mean absolute percentage error (MAPE) [30, 48, 50] as the main metric of prediction accuracy. We also report $\pm 5\%$ Acc. and $\pm 10\%$ Acc. to avoid the impact of test set size variations [67].

⁵“Sensitivity” refers to NF performance as a function of contention level for simplicity [33, 48–50].

NF	SLOMO			Yala		
	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)
ACL	1.3	100.0	100.0	1.2	100.0	100.0
NIDS	16.2	24.3	74.3	1.5	95.9	100.0
IPTunnel	62.9	70.5	73.1	3.8	75.6	92.3
IPRouter	4.2	68.4	98.2	3.8	66.7	100.0
FlowClassifier	7.5	28.1	73.7	3.8	63.2	100.0
FlowTracker	4.9	56.1	86.0	3.9	61.4	100.0
FlowStats	11.7	33.3	57.9	4.3	70.2	96.5
FlowMonitor	40.9	31.1	41.9	4.5	62.2	93.2
NAT	8.2	38.6	49.1	6.4	42.1	80.7

Table 2. Prediction accuracy comparison under both multi-resource contention and varying traffic attributes. On average Yala reduces MAPE by 78.8% compared to SLOMO, at 3.7% and 17.5%, respectively. Unless otherwise stated, rows of table are sorted in ascending order of Yala’s MAPE.

7.2 Overall Accuracy

We first evaluate the overall prediction accuracy of Yala under multi-resource contention and varying traffic attributes. Each target NF is co-located with up to three other NFs and we numerate all possible combinations of NFs. We also apply 9 distinct traffic profiles for each NF. The results are aggregated under all traffic profiles, as shown in Table 2. We can see that Yala averagely exhibits 3.7% MAPE, 70.8% $\pm 5\%$ Acc. and $95.9\% \pm 10\%$ Acc., compared to SLOMO’s 17.5% MAPE, 50.0% $\pm 5\%$ Acc. and $72.7\% \pm 10\%$ Acc., demonstrating Yala’s superior prediction accuracy. Specifically, Yala has the most significant gains for IPTunnel, FlowMonitor, FlowStats, and NIDS that use multiple resources and/or is sensitive to traffic attributes. Meanwhile, Yala achieves the same accuracy as SLOMO for ACL because it is very lightweight and insensitive to traffic attributes. Note that the high prediction accuracy for such NFs is aligned with that from previous studies [33, 48, 50].

Next, we microbenchmark Yala’s major design choices to better understand the benefits they each bring.

7.3 Deep-Dive: Multi-Resource Contention

First we look at how Yala’s per-resource modeling and composition approach handles multi-resource contention. We fix the traffic profile to be the default in this section to isolate its impact. We choose FlowMonitor and NIDS that utilize multiple resources, and co-run each with mem-bench and regex-bench with varying contention levels. Table 3 presents the comparison. We can observe that Yala reduces the MAPE by 44.2% and 17.1% for FlowMonitor and NIDS, respectively. To better analyze the source of accuracy gains, we zoom in on FlowMonitor and vary the regex contention level it receives in two ranges: low range ($MTBR \leq 600$ matches/MB), and high range ($MTBR > 600$ matches/MB). Figure 7(a) depicts the distribution of the absolute percentage errors. Yala

NF	SLOMO			Yala		
	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)
NIDS	21.4	60.0	71.2	4.3	55.6	95.6
FlowMonitor	49.3	18.5	33.3	5.1	59.3	88.9

Table 3. Prediction accuracy of SLOMO and Yala when the NF runs under only multi-resource contention. Traffic profile is fixed to the default one.

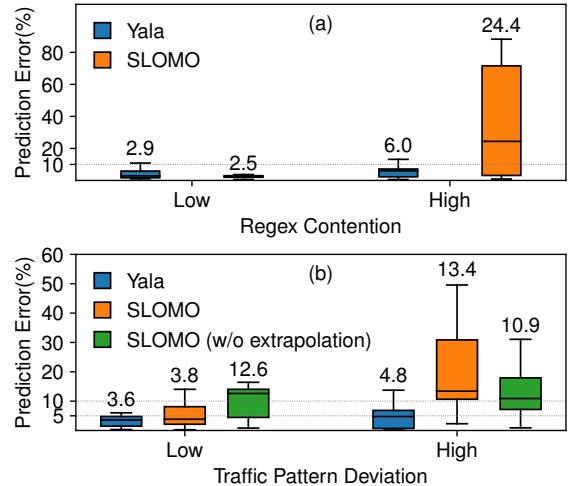


Figure 7. The distribution (box and whisker plot) of the absolute percentage errors of (a) multi-resource contention with different regex contention levels, and (b) memory-only contention with different ranges of variations in the flow count. We show the value of median error in both figures.

maintains low errors as contention rises with median errors consistently below 6.0%. With low contention, SLOMO also achieves high accuracy with median error at 2.5%, because in this case multi-resource contention effectively reduces to single-resource (memory for FlowMonitor) contention. Here Yala’s error is actually slightly higher than SLOMO, because SLOMO enjoys the same amount of training data as Yala but concentrate on one fixed traffic profile. During high contention, SLOMO’s inability to model contention on these two resources simultaneously lead to high median errors at 24.4%.

To further evaluate the use of Yala’s composition design based on execution pattern (§4.2), we write two synthetic NFs, NF1 and NF2, with NF1 using memory and regex, while NF2 adds the compression accelerator. Each has both a pipeline and run-to-completion version. We compare Yala to the simple sum and min composition (recall §2.2.1), where they use the same per-resource models trained specifically for NF1 and NF2. As shown in Table 4, Yala attains the best accuracy across all cases and resource usage patterns, with

NF	Pattern	MAPE (%)		
		sum	min	Yala
NF1	pipeline	9.8	0.7	0.7
	run-to-completion	8.7	12.4	1.3
NF2	pipeline	21.9	1.8	1.8
	run-to-completion	14.6	7.6	1.6

Table 4. Prediction error of different multi-resource composition approaches for different execution patterns.

MAPE lower than 2%. This gain essentially comes from properly modeling NF’s execution pattern to capture the end-to-end impact of multi-resource contention.

7.4 Deep-Dive: Traffic Attributes

We now move to examine Yala’s design on traffic-aware modeling. We choose traffic-sensitive NFs and co-run each with mem-bench on a single BF-2. Since SLOMO only considers memory contention, we set a fixed contention level in memory, exclude other resource contention, and generate 100 traffic profiles by randomly changing number of flows, packet size, and MTBR when applicable for each NF. Table 5 shows the results aggregated from all profiles. Again Yala attains superior accuracy over SLOMO across the board, with over 90% in $\pm 10\%$ Acc. and <5% MAPE for most NFs.

We then zoom into one particular attribute, flow count, which SLOMO also specifically models. We vary the flow count between training and testing across two ranges: low range where it changes by at most 20%, and high range (>20%). Figure 7(b) displays the distribution of absolute percentage error in this case. Yala maintains low errors consistently, with a median at 4.7%, highlighting the benefits of our traffic-aware modeling (§5). Under low-range variations, SLOMO exhibits high accuracy with sensitivity extrapolation [48]. However, as traffic profiles undergo more significant changes, SLOMO suffers from high prediction errors, with 13.4% at the median. This is consistent with [48]: the extrapolation only works when the NF’s sensitivity profile in training has enough overlap with that under testing traffic [48], which corresponds to low range profiles here.

7.5 Yala Use Cases

We now illustrate Yala’s practical benefits through two use cases: (1) It enables contention-aware scheduling of NFs to improve resource utilization; (2) it facilitates performance diagnosis for NFs with dynamic traffic.

7.5.1 Contention-Aware Scheduling We consider the scenario in which the operator places the NFs as they arrive to a group of SmartNICs to maximize resource utilization (*i.e.*, minimize SmartNICs used) while maintaining their SLAs. SLA here is defined as the maximum allowed throughput drop relative to the baseline when the NF runs solo. Given

NF	SLOMO			Yala		
	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)	MAPE (%)	$\pm 5\%$ Acc. (%)	$\pm 10\%$ Acc. (%)
NIDS	2.5	90.0	100.0	1.1	98.0	100.0
FlowClassifier	10.4	52.0	66.0	2.9	80.0	100.0
NAT	9.5	28.0	64.0	3.1	82.0	96.0
FlowTracker	4.0	70.0	92.0	3.5	74.0	96.0
FlowStats	9.5	44.0	66.0	4.7	72.0	92.0
FlowMonitor	11.9	20.0	44.0	4.8	62.0	88.0
IP Tunnel	88.0	24.0	52.0	5.6	80.0	94.0

Table 5. Prediction accuracy of SLOMO and Yala when target NF runs under memory-only contention and dynamic traffic profiles.

Approach	Resource Wastage (%)	SLA Violations (%)
Monopolization	196.3	0
Greedy	19.0	16.5
SLOMO	-21.8	24.4
Yala	0.5	1.9

Table 6. Yala’s usecase in contention-aware scheduling compared to other baseline strategies. SLOMO’s negative resource overhead stems from erroneous placements compared to the optimal deployment.

that the offline version of this problem is NP-complete bin-packing [32, 66], we follow previous works [48, 63, 69] and consider online heuristics that deploy the NFs one by one. Specifically, we compare the following strategies: (1) Monopolization, which forbids co-location of NFs; (2) Greedy, which places an NF onto the SmartNIC with most available resources [47, 60]; (3) Contention-aware, which first predicts the performance of all NFs on a SmartNIC if the current NF gets deployed onto this SmartNIC, and then deploys the NF onto the SmartNIC if no SLA violation is predicted. Both Yala and SLOMO can provide such contention-aware predictions. A new SmartNIC is added to the cluster when there is no feasible placement.

Table 6 compares the above strategies over 100 random sequences of 500 NF arrivals each. Each NF is assigned the default traffic profile, and its SLA is set to 5-20% throughput drop. We examine resource wastage, *i.e.*, how many additional NICs are used against the optimal plan found by exhaustive search, and the corresponding SLA violations. We observe that Yala minimizes resource wastage to merely 0.5% and reduces SLA violations by 88.5% and 92.2% over Greedy and SLOMO on average. The near-optimal performance of Yala illustrates its potential in coordinating NF scheduling in a real-world scenario.

7.5.2 Performance Diagnosis In practice, performance diagnosis has important values as it allows programmers to systematically explore the design spaces, identify performance bottlenecks and optimization opportunities, and even provide early-stage insights/guidances on next-generation

NF	Correctness (%)	
	SLOMO	Yala
Flowstats	100.0	100.0
FlowMonitor	38.7	100.0
IPComp Gateway	29.3	100.0

Table 7. Percentage of correct identifications of performance bottleneck using SLOMO and Yala.

NF	Full		Random		Adaptive	
	P.C.: 3200×		P.C.: 1×		P.C.: 1×	
	MAPE (%)	±10% Acc. (%)	MAPE (%)	±10% Acc. (%)	MAPE (%)	±10% Acc. (%)
FlowClassifier	2.3	100.0	14.4	28.0	2.9	100.0
NAT	2.9	98.0	9.6	62.0	3.1	96.0
FlowTracker	3.4	96.0	38.9	0.0	3.4	86.0
FlowMonitor	4.5	86.0	12.3	42.0	4.8	88.0
FlowStats	5.3	90.0	9.8	68.0	4.9	90.0
IPTunnel	5.3	98.0	8.5	82.0	5.9	96.0

Table 8. Profiling cost and model accuracy using full, random and Yala’s adaptive profiling. P.C. refers to profiling cost.

SmartNIC [48, 51]. Here we show another usecase of Yala in diagnosing performance bottlenecks in NFs with dynamic traffic, when the bottleneck may shift across resources.

As Table 7 shows we deploy FlowStats, FlowMonitor, and IPComp Gateway that all use regex accelerator. We co-run each of them with mem-bench and regex-bench and adjust the MTBR from 0 to 1100 matches/MB while keeping memory contention levels unchanged, and manually analyze the actual its performance bottleneck using the hotspot analysis function of perf-tools [20]. This is the ground truth. We then calculate the percentage of correct identification of bottleneck using our prediction models. We can see Yala accurately identifies bottleneck for all three NFs with its multi-resource performance modeling, while SLOMO only works for FlowStats, as it is always bottlenecked on memory. FlowMonitor and IPComp Gateway’s bottleneck actually shifts with traffic. For example, we observe that FlowMonitor’s bottleneck is memory with MTBR at 80 matches/MB, but changes to regex with MTBR at 1000 matches/MB (default traffic profile). Thus this usecase demonstrates Yala’s capability in pinpointing NF bottlenecks with dynamic traffic.

7.6 Adaptive Profiling

Lastly we examine the adaptive profiling design of Yala. We select traffic-sensitive NFs from Table 1, and train them using three different approaches – full profiling, random profiling, and adaptive profiling (§5.2). For random profiling and Yala’s adaptive profiling, we set the same number of training data points (*a.k.a.* profiling quota) to ensure a fair comparison. For full profiling, we use 80% of the profiled data for training, and

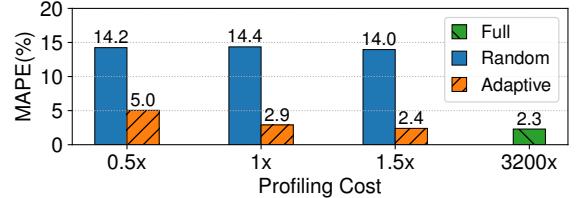


Figure 8. Prediction error on FlowClassifier using full, random and Yala’s adaptive profiling. We change the profiling quota of random and adaptive profiling to 0.5× and 1.5× of that used in Table 8.

the remaining 20% for testing. Profiling cost is represented by the number of training data samples normalized against adaptive/random profiling’s quota. We observe from Table 8 that Yala’s adaptive profiling offers comparable accuracy to full profiling which uses 3200× more data⁶. Compared to random, adaptive profiling significantly enhances accuracy within the same profiling quota. We further show the benefit of adaptive profiling using FlowClassifier as an example in Figure 8. We adopt the same setting as Table 8 but change the profiling quota to 0.5× and 1.5×. Figure 8 reveals that by increasing current profiling quota by 50% (still ~2100× less than the profiling cost of full profiling), adaptive profiling achieve similar error compared to full profiling, at 2.4% and 2.3%, respectively, while random profiling does not exhibit accuracy improvement since performance-significant ranges of traffic attribute is still not covered in the training data.

Time cost of profiling. As discussed in §4, Yala requires offline profiling for each NF to build per-resource models and identify the execution pattern. This process primarily involves the collection of: (1) the contention level of synthetic benchmark NFs (mem-bench, etc.), and (2) the contention level and sensitivity profiles of the target NF. Across our experiments, we find that on average 1.6 hours and 0.5 hours for each, respectively. These time investments are acceptable since profiling is a one-time effort.

8 Discussion

We discuss a few issues one may have regarding Yala.

What if the configuration of an NF changes? It is possible that an NF’s configuration is adjusted for various reasons, e.g. adjusting ACL rules in a Firewall NF to apply new policies. Such changes can cause performance characteristics to change, making the existing model inaccurate. To make Yala “configuration-aware”, one may adopt a similar approach of traffic attributes, *i.e.*, extracting “configuration attributes” for an NF and integrating it into the per-resource models. We leave this as future work.

⁶This is because we use 16 values for packet sizes and 200 values for the number of flows in full profiling. For each (packet size, number of flows) tuple, full profiling repeats profiling over a set of random memory contention levels.

NF	SLOMO			Yala		
	MAPE	$\pm 5\%$	$\pm 10\%$	MAPE	$\pm 5\%$	$\pm 10\%$
	(%)	Acc.(%)	Acc.(%)	(%)	Acc.(%)	Acc.(%)
Firewall	18.4	58.7	64.7	0.9	100.0	100.0

Table 9. Prediction accuracy of SLOMO and Yala when target NF runs under memory-only contention and dynamic traffic profiles on Pensando SmartNIC.

Can Yala be generalized to other SmartNICs? Yala can be generalized to other SoC SmartNICs due to the similar architecture of their hardware accelerators and memory subsystem. To quickly validate such generalizability, we collect data and train performance models of a Firewall NF [29] running on an AMD Pensando SmartNIC [12]. The NF conducts a flow walk on hardware flow table and updates entry metadata upon matching against flows in the input traffic. As shown in Table 9, the average prediction error of Yala is 0.9%, which is 17.5% lower compared to that of SLOMO. This result reflects that applying Yala to other SoC SmartNICs is feasible. However, for SmartNICs like on-path SmartNICs whose architecture significantly deviates from SoC SmartNICs, more investigation is needed into the contention behavior of their specialized hardware resources [56, 64].

Can Yala adapt to system-wide state changes that affect the maximum performance of NFs? Yala predicts the maximum throughput of co-located NFs to ensure they conform to SLA under multi-tenancy. However, SmartNICs may experience system-wide state changes due to various reasons, altering the maximum throughput of NFs. A typical example is dynamic voltage and frequency scaling (DVFS) [14, 43], which may affect the NF’s maximum performance due to CPU frequency down-scale or up-scale. Different DVFS policies can be enabled by setting the frequency scaling governor of CPUs on servers, which is however not supported on common SoC SmartNICs currently, e.g. the SmartNICs we use in our experiments (Nvidia Bluefield-2 and AMD Pensando) [6]. If we are to extend Yala to predict maximum performance of on-NIC NFs on future generations of SmartNICs that support DVFS and other similar system-wide state changes, related variables, e.g. OS policy and thermal state for DVFS, should be integrated in our models to ensure high accuracy under different system states, e.g. power state in DVFS.

9 Related Work

NF performance modeling. There have been extensive efforts on modeling NF performance. We compare Yala with past frameworks in Table 10. Yala is, to our knowledge, the first contention-aware framework that explicitly models multi-resource contention and traffic attributes.

Framework	Contention-aware	Multi-resource	Traffic-aware	Sourcecode-agnostic
Clara [55]	✗	✓	✓	✗
LogNIC [37]	✗	✓	✓	✓
BubbleUp [50]	✓	✗	✗	✓
SLOMO [48]	✓	✗	✗	✓
Yala	✓	✓	✓	✓

Table 10. NF performance prediction frameworks. “Sourcecode-agnostic” means the framework does not require NF’s source code. SLOMO only considers 20% variation in flow counts so it is considered “half” traffic-aware.

Isolation. Resource isolation techniques have been explored to provide performance guarantees of co-running applications [31, 36, 39, 41, 54, 63]. For example, FairNIC [36] proposes isolation solutions for SmartNIC accelerators. PARTIES [31] and ResQ [63] leverages off-the-shelf isolation techniques, e.g., Intel CAT [17] to enable QoS-aware resource partitioning. However, these efforts are either inapplicable to SmartNICs, or provide only partial isolation, or require substantial rewriting of NFs.

SmartNIC-accelerated NFV. NFV platforms have been leveraging SmartNICs to improve energy efficiency and enable host resource-saving [29, 40, 42, 46, 47]. For example, E3 [47] builds a SmartNIC-accelerated microservice execution platform with high energy efficiency. Yala is complementary to them as it can assist operators to make better runtime decisions, thus improving resource utilization and reducing SLA violations.

10 Conclusion

Prior contention-aware performance prediction frameworks fail to accurately predict the performance of on-NIC NFs due to multi-resource contention and changing traffic profiles. We systematically analyze multi-resource contention characteristics on SmartNIC as well as the impact of traffic attributes on performance of on-NIC NFs. Our insights enable the design of Yala, a multi-resource contention-aware and traffic-aware performance prediction framework for on-NIC NFs. Yala achieves accurate performance predictions, with 3.7% prediction error and 78.8% accuracy improvement on average compared to prior works, and enables new usecases.

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