Efficient Network Function Backup by Update Piggybacking

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Abstract—Network Function Virtualization (NFV) and Service Function Chaining (SFC) have been widely used to enable flexible and agile network management. To enhance reliability, some research has proposed to deploy backup function instances for prompt recovery when a primary instance fails. While most of the recent studies focus on speeding up recovery, less attention has been paid to the problem of minimizing the state update cost. In this work, we present PiggyBackup (Piggyback-based Backup), an efficient backup instance deployment and update protocol. Our key idea is to reuse the existing service chains traversing through servers in a network to help piggyback the update information. By doing this, we eliminate the header overhead and reduce the amount of update traffic significantly. To realize such a piggyback-based update more efficiently, we investigate the backup instance deployment and chain selection problems to enhance piggybacking opportunities and reduce the forwarding hop counts with explicit consideration of the distribution of service chains. Our simulation results show that PiggyBackup reduces the average overall update overhead by 47.65% and 39.56%, respectively, in a fat-tree topology as compared to random deployment and shortest path based deployment.

Index Terms—Piggybacking, State update, Function backup, Instance deployment

1 INTRODUCTION

Network Functions (NFs) typically provide services such as load balancers, firewalls, Network Address Translation (NAT), and deep packet inspection in a network. Conventionally, those services can only be implemented in specific hardware, which is however not flexible and hardly customized for clients. With the emergence of Software-Defined Networking (SDN), it has become elastic and efficient to support software-based services in Virtual Machines (VMs), which is known as Network Function Virtualization (NFV) [1]. The design of NFV enables network operators to install virtualized NFs and provide clients customized services by Service Function Chaining (SFC). A client or network application can request a set of network functions executed sequentially according to its dynamic demands.

For a network enabling NFV, system reliability is of importance since virtual machines are prone to errors and recovering virtual NFs usually takes a non-negligible latency [2]. Hence, providing fault tolerance is essential for an NFV-enabled network. Some other middlebox frameworks [3], [4], [5], [6], [7] have investigated how to provide fault tolerance for individual middleboxes. Most of fault-tolerant designs enhance reliability by introducing redundancy [8], [9], [10], [11], [12], [13]. In particular, to ensure the reliability of a network function, one can deploy a primary NF instance in a VM and further install a redundant NF instance as a backup in a different VM. Or, two NF instances can be installed in different VMs, both used to serve their own clients but, at the same time, acting as the backup of each other. This type of fault tolerance is called active-active backup as both the primary and redundant NF instances are actively used. However, for active-active backup, primary and redundant NF instances usually operate independently and do not synchronize their states. That is, the states will not be consistent when services are migrated to redundant instances due to the failure of their primary NF instances. For example, a service may have been authorized by its primary NF instance to access a private database but is rejected by its backup instance as the verification information is not known by the backup. To resolve this limitation, an alternative, called active-standby backup [10], [11], [12], [13], has been proposed to allow a backup to only keep the state information of primary NF instances but do not serve clients. Those standby backup instances can be activated immediately with the up-to-date states once their primary instances fail.

Recent efforts [10], [11], [12] have investigated an efficient and light-weight scheme to launch standby backup instances. However, an open problem still remains unsolved: efficient state update. To ensure state consistency, each stateful primary instance should periodically forward state information to its corresponding backup instance. Those periodic state updates would incur tremendous traffic loads. We notice that the update cost closely depends on the locations of primary and backup instances. Intuitively, we can reduce the update cost by installing a backup instance close to its primary instance. However, as the computing resources of a server are limited, a backup instance may have to serve multiple primary instances who compete with each other. Hence, our goal is to investigate an efficient backup instance deployment and update protocol so as to minimize the overall state update cost.

In this paper, we present PiggyBackup (Piggyback-based Backup), an efficient backup instance deployment and update protocol. Our design is motivated by a key observation: a network has typically served a large number of service function chains that traverse through diverse routes and can
help piggyback the backup update information. As state updates usually generate periodical but small packets, the headers of those small update packets become the major overhead of state updates. By piggybacking the state information in existing SFCs, we can exclude the header for an update and significantly reduce the update cost, as illustrated in Fig. 1. More importantly, while a network may admit several service chains over time, we do not need to select a dedicated chain to piggyback the update. Instead, any chain with traffic traversing from a primary instance to a backup instance can be dynamically selected to help forward the updates.

To realize this idea, we have to address two practical challenges. First, to enable piggybacking, a piggybackable backup instance should be deployed in a VM traversed by existing SFCs who have passed through its primary instances. For example, for the primary NF B in node 2 in Fig. 1, if its backup function is deployed in node 5, the lower solid orange service chain can help piggyback updates in its payload and carry the updates from the primary node 2 to the backup node 5. Though there may exist several chains traversing through a primary instance and can help piggyback the backup information, their routing paths, however, have already been assigned based on their customized demands. Hence, the cost of information updates does not depend on the distance between the primary instance and backup instance anymore but is determined by the path length of piggybacking chains from a primary instance to its backup instance. Second, since many SFCs can be candidates that help piggyback the update information, the one with a shorter piggybacking path should be preferable. However, as traffic arrivals of an SFC are usually unpredictable, selecting proper chains to piggyback the updates becomes difficult. Finally, as VM resources are limited and the distribution of SFCs cannot be controlled, some primary NF instances may not have any chance to piggyback their updates, e.g., NF E in node 6 in Fig. 1. Since no service chain traversing from node 6 to an available node, we can only deploy the backup function of NF E in some available node, e.g., node 3, and push its updates using stand-alone packets, which require additional header overhead, to the backup node along the dotted green path.

To address those challenges, we develop a backup instance deployment algorithm that enhances the opportunities of piggybacking and minimizes the cost of stand-alone updates. Our piggyback-based placement explicitly considers the locations of primary function instances and the distribution of chains, as a result allowing backup instances to be more likely traversed by chains and realizing piggybacking. We then propose a chain selection scheme based on chain arrival prediction to reduce the piggybacking cost. For those non-piggybackable instances, we further deploy stand-alone backup instances to ensure full reliability.

Our contributions are as follows:

- We enable piggybacking update by a sophisticated back instance deployment algorithm that optimizes piggybacking opportunities.
- We design a chain selection scheme to identify a short chain that is most likely to piggyback the update information on time. The scheme can hence balance the tradeoff between the piggybacking cost and the update latency.

- We conduct extensive simulations to verify the effectiveness of our design in a fat-tree topology. The simulation results show that PiggyBackup outperforms both random deployment and shortest path based deployment. The overall update overhead can be reduced by about 40%–50%.

The rest of the paper is organized as follows. Section 2 reviews recent work on NFV fault-tolerant designs and NF deployment. Section 3 formally defines the backup instance deployment problem, and Section 4 details the design of PiggyBackup. We evaluate the performance in Section 5 and conclude this work in Section 6.

## 2 RELATED WORK

Recent research related to backup NF deployment falls in three categories:

### 2.1 Fault Tolerance Designs

Several recent studies have investigated how to ensure network reliability [14], [15], [16], [17]. The challenges of software reliability assurance for NFV is first introduced in [14]. The work [15] offers a checkpoint-based fault-tolerant network with three high-level goals: generality, transparency, and seamless failure recovery. [17] is the first fault-tolerant system for Virtualized NFs (VNFs). It maintains the states of network flows in different NF instances by using light checkpoints. In general, reliability can be supported by two different ways: active-active [8], [9] or active-standby [10], [11], [12], [13]. The active-active solutions [8], [9] deploy multiple NF instances to ensure a chain to be migrated to a different NF instance when its primary instance fails. All NF instances should support their own chains and be used as a backup at the same time. They hence require the same level of computing resources. However, there exists no state transferring among different instances, i.e., no state consistency guaranteed. The active-standby solutions deploy lightweight backup instances, which only keep the states of primary functions but do not serve SFCs. It hence requires negligible computing resources and guarantees state consistency. The work [13] adopts this solution and deploys backup instances to optimize the reliability of the whole network without considering the update cost.
Our work also adopts active-standby backup but aims at minimizing the update overhead.

2.2 State Maintenance

State consistency can be maintained by three types of implementation [12]: hardware [18], VNFs [19], and software [10] [11] [12]. Hardware-based implementation [18] is the most traditional method, which is more efficient but cannot be customized. The VNF-based implementation allows network managers to flexibly program network functions that customize how the states should be protected and maintained. For instance, the work [19] leverages a state transformation technique to avoid the need for manual intervention. Modifying NF programs, however, requires a high manpower cost and makes version control difficult. Finally, the software-based implementation is the most commonly used solution nowadays. The systems [10] [11] implement a robust state transferring scheme for SDNs without modifying the NFs. Stratus [12] is a cloud-based solution developed to achieve state consistency in stateful VNFS. Due to the popularity of software-based solutions, we adopt this type of implementation and investigate how to deploy backup NFs so as to reduce the state update cost subject to the reliability requirement.

2.3 Primary NF Instance Deployment

The latency of service function chaining is closely related to how NF instances are deployed. Recently, a large number of studies have devoted to enhancing efficiency and resource utilization of NF deployment in an SDN [20], [21], [22], [23], [24], [25], [26], [27], [28], [29]. The work [28] derives an integer linear programming model to solve the joint NF placement, assignment, and routing problems. It first identifies suitable positions to deploy VNFS and then assigns proper instances to the NF requests of a chain subject to a given latency constraint. LightChain [29] determines VNF placement locations to minimize the number of hop counts of every SFC but does not consider resource utilization. While the objective of primary NF deployment is to improve the efficiency of service chaining, the objective of backup NF deployment is however to ensure high reliability and low update costs, which are the focus of our work.

3 Problem Statement and System Model

In this section, we first formally define the backup instance deployment problem and then express the system model of PiggyBackup.

3.1 Problem Statement

An SDN network is represented as a directed graph \( G = (V, E) \), where \( V \) is the set of physical machines (servers) and \( E \) is the set of network edges. The network serves a set of function types \( F \) and installs multiple instances for every type \( f \in F \) in different physical servers. We collect the set of deployed primary function instances as a set \( \mathcal{N} \), and, for simplicity, \( \mathcal{N}_f \subseteq \mathcal{N} \) represents the set of instances of function type \( f \), i.e., \( \cup_f \mathcal{N}_f = \mathcal{N} \). Let \( \mathcal{C} \) be the set of currently served service chains. We assume that the deployment of primary function instances is given and the instances serving each SFC \( c \in \mathcal{C} \) have also been assigned. Let notations \( u(n) \) and \( f(n) \), respectively, denote the server \( v \in V \) that installs the primary function instance \( n \in \mathcal{N} \) and the function type of \( n \). Our goal is to install a backup function instance for every primary function instance \( n \in \mathcal{N} \) in a physical server \( v \in \mathcal{V} \) different from \( u(n) \).

Since each physical server has limited capacity, we assume that each \( v \in \mathcal{V} \) can at most install \( B_v \) backup function instances. We define the set of backup instances installed in \( v \) as \( B_v \), and, hence, the set of all backup instances is \( B = \bigcup_{v \in \mathcal{V}} B_v \). Due to limited resources, we assume that each backup function instance \( b \in B \) can backup the states for multiple primary function instances of the same type. However, each backup instance can support at most \( K \) primary instances. Each primary instance \( n \in \mathcal{N} \) will be assigned a backup instance and periodically send the up-to-date states to its associated backup instance. The update cost of an instance \( n \), denoted by \( w_n \), is defined as the aggregated number of bits over all network edges per update. That is, if the update of an instance \( n \) including \( L \) bits traversing through \( k \) hops in the network, the total update cost \( w_n \) will equal to \( w_n = L \times k \). We aim at identifying the optimal backup instance deployment such that the overall update forwarding cost can be minimized.

3.2 System Model

In our system, each function type \( f \) can be backed up in many servers, but each primary function instance \( n \) of the function type \( f \) should be associated exactly with one backup server. A backup server of function type \( f \) can be associated with up to \( K \) primary instances. Our goal is to jointly solve the problems of backup instance deployment and primary-backup instance association. The two problems can be represented by the following binary decision variables:

\[
I_{f,v} = \begin{cases} 
1, & \text{if function type } f \in F \text{ backed up in } v \in \mathcal{V}, \\
0, & \text{otherwise, and}
\end{cases}
\]

\[
J_{n,v} = \begin{cases} 
1, & \text{if primary instance } n \in \mathcal{N} \text{ backed up in } v \in \mathcal{V}, \\
0, & \text{otherwise.}
\end{cases}
\]

By identifying a proper configuration of the above two variables, we can create more piggyback opportunities, as a result reducing the update cost. The notations are summarized in Table 1. Such a piggyback-based backup instance deployment and assignment problem can be formulated as the following integer linear programming (ILP) problem:

\[
\min \sum_{n \in \mathcal{N}} w_n = \min \sum_{n \in \mathcal{N}} w_n^{\text{pr}} + w_n^{\text{alone}} \quad (1a)
\]

subject to:

\[
\sum_{f \in F} I_{f,v} \leq B_v, \quad \forall v \in \mathcal{V} \quad (1b)
\]

\[
\sum_{v \in \mathcal{V}} J_{n,v} = 1, \quad \forall n \in \mathcal{N} \quad (1c)
\]

\[
\sum_{n \in \mathcal{N}} J_{n,v} \leq K \times I_{f,v}, \quad \forall v \in \mathcal{V}, f \in F \quad (1d)
\]
TABLE 1
List of Notations

| Notation   | Definition                                                                 |
|------------|---------------------------------------------------------------------------|
| G          | network graph including a set of physical servers                           |
| F          | set of function types                                                      |
| N          | set of installed primary function instances                               |
| u(n)       | server that installs instance n                                            |
| f(n)       | function type of instance n                                               |
| C          | set of existing chains                                                     |
| C_{u,v}    | set of existing chains traversing from u to v                             |
| l_{c,u,v}  | number of hops traversed by chain c from u to v                           |
| \omega_{min}^c | shortest path length from u to v                                          |
| \omega_{PG}  | cost of a piggyback update message                                        |
| \omega_{alone} | cost of a stand-alone update message                                      |
| B_v       | set of backup instances installed in server v                             |
| B       | maximal number of backup instances allowed in server v                    |
| K        | maximal number of primary instances a backup instance can support         |

\[
\begin{align*}
\omega_{PG}^n & = \sum_{v \in V} J_{n,v} \left( \sum_{c \in C_{u(n),v}} l_{c,u(n),v} \omega_{PG} / |C| \right), \forall n \in N \tag{1e} \\
\omega_{alone}^n & = \sum_{v \in V} J_{n,v} \left( |C| C_{u(n),v} / \omega_{min,u(n),v} \omega_{alone} / |C| \right), \forall n \in N \tag{1f}
\end{align*}
\]

\[
I_{f,v} \in \{0, 1\}, J_{n,v} \in \{0, 1\} \tag{1g}
\]

We assume that each backup server has a limited computation power and storage. Hence, Eq. (1b) limits the number of backup instances deployed in v by its capacity B_v. Eq. (1c) requires each primary function instance n to be assigned exactly one backup node. Then, Eq. (1d) constrains a primary instance n of type f to be associated with a backup node v only if v has installed a backup instance of its function type, i.e., I_{f,v} = 1. Otherwise, the primary instance n cannot associate with v when I_{f,v} = 0. Also, this expression forces the number of primary instances associated with a server v to be no more than its capacity K. In our design, we allow a service chain traversing through u(n) to v to help piggyback the update information from primary instance n to its backup node v. Let \( C_{u(n),v} \) represent the set of those piggybacking chains. Since different chains traverse through different paths, the piggybacking cost of chain c in \( C_{u(n),v} \) can be calculated by \( l_{c,u(n),v} \omega_{PG} \), as expressed in Eq. (1e), where \( l_{c,u(n),v} \) is the number of hops traversed by chain c from u(n) to v. If, unfortunately, no chain can help piggyback the update information, we should send stand-alone update packets, each of which costs \( \omega_{alone} \) as in Eq. (1f), where \( l_{u(n),v}^{\omega_{min}} \) is the shortest path length between u(n) and v. We further normalize the two costs \( \omega_{PG} \) and \( \omega_{alone} \) in Eqs. (1e,1f) by the cardinality of C to derive the expected cost. Finally, the objective in Eq. (1a) aims at minimizing the overall update cost.

The optimal solution of the above ILP problem can be solved by exhaustive search or some generic algorithm, e.g., branch and bound [30], which however introduces a high complexity. We hence focus on developing a more practical light-weight greedy algorithm that identifies an efficient and near-optimal backup strategy with a joint consideration of the update cost and resource utilization. Our greedy algorithm contains two modes, piggyback mode and stand-alone mode. The piggyback mode deploys as many backup instances that can be traversed by SFCs as possible. It further identifies a suitable chain to piggyback the updates with small costs. For the remaining primary instances who cannot be supported by piggyback-based backup, the stand-alone mode then installs backup instances in the remaining available servers for reducing their update costs.

4 PiggyBackup Design

We now describe the proposed PiggyBackup design that deploys piggyback backup instances to enhance piggybacking opportunities (Section 4.1) and selects proper piggybacking service chains (Section 4.2). We then explain how to deploy the remaining stand-alone backup instances to ensure full coverage (Section 4.3).

4.1 Piggyback Instance Deployment

Since the opportunities of piggybacking updates are closely correlated to how service chains traverse, we hence propose a greedy algorithm to deploy backup instances based on the distribution and loading of service chains, as summarized in Algorithm 1. Since each server has a limited capacity, we should deploy a backup instance of type f on a server v if more service chains can traverse from different primary instances of the same type to v. To this end, we collect all the chains c in C that traverse through any instance n in \( N_f \) of type f as a set \( C_f \) and deploy backup function instances for various function types f in descending order of |\( C_f \)| (line 2).

To identify a proper server v to install the backup instance of type f, we try to quantify the amount of potential

Algorithm 1: Piggyback backup instance deployment

| Step | Description |
|------|-------------|
| 1    | while \( F \neq \emptyset \) do |
| 2    | \( C_f \leftarrow \) set of chain including function type f |
| 3    | \( f \leftarrow \arg \max_f |C_f| \) |
| 4    | \( F \leftarrow F \setminus \{f\} \) |
| 5    | while \( N_f \neq \emptyset \) do |
| 6    | \( \lambda_{v,n} \leftarrow \sum_{c \in C_f} r_c / l_{c,u(n),v}, \forall n \in N_f, v \in V, B_v > 0 \) |
| 7    | \( \lambda_v \leftarrow \sum_{n \in N_f} \lambda_{v,n}, \forall v \in V, B_v > 0 \) |
| 8    | if \( \max_v \lambda_v = 0 \) then break; |
| 9    | // select a node with highest score to back up for f |
| 10   | \( v^* \leftarrow \arg \max_v \lambda_v \) |
| 11   | install backup instance in \( v^* \), \( B_{v^*} \leftarrow B_{v^*} - 1 \) |
| 12   | \( I_{f,v^*} \leftarrow 1 \) |
| 13   | // associate top K instances with backup instance in \( v^* \) |
| 14   | sort \( n \in N_f \) in descending order of \( \lambda_{v^*,n} \) |
| 15   | \( J_{n,v^*} \leftarrow 1, k = 1, 2, \cdots, K \) |
| 16   | remove \( n_1, \cdots, n_K \) from \( N_f \) |
| 17   | return \( I_{f,v}, J_{n,v}, \forall n \in N_f, f \in F, v \in V \) |
traffic that can piggyback updates of any primary instance \( n \in \mathcal{N}_f \) to server \( v \). For simplicity, we call the traffic of any \( c \in \mathcal{C}_f \) that arrives at a backup server \( v \) after being served by an instance \( n \in \mathcal{N}_f \) piggybackable traffic to server \( v \) for short. To create more piggyback opportunities, we should deploy a backup instance in a server \( v \) traversed by more piggybackable traffic. However, the cost of piggybacking updates also depends on the distance between the location of a primary instance and server \( v \). Hence, to quantitatively prioritize all the servers available for installing a backup instance, we sort the available servers in descending order of the following performance metric (lines 5-6):

\[
\lambda_v = \sum_{n \in \mathcal{N}_f} \lambda_{v,n}, \text{ where } (2)
\]

\[
\lambda_{v,n} = \frac{\lambda_c (l_{c,u(n),v})}{\sum_{c \in \mathcal{C}_f} l_{c,u(n),v}}, \text{ (3)}
\]

and \( \lambda_v \) is the average traffic rate of chain \( c \) and \( l_{c,u(n),v} \) is the length of the segment traversed by chain \( c \) from the server of its primary instance \( u(n) \) to a potential backup server \( v \). Note that \( l_{c,u(n),v} \) is set to \( \infty \) if chain \( c \) does not arrive \( v \) after \( u(n) \), i.e., not piggybackable. At a high level, the metric \( \lambda_{v,n} \) represents the sum traffic arrival \( r_c \) of chain \( c \) passing through a server \( v \) divided by the path length of piggybacking \( l_{c,u(n),v} \), while the metric \( \lambda_v \) is total value summed over all possible instances \( n \in \mathcal{N}_f \). That is, a server with more piggybackable traffic and a shorter piggyback path length will result in a larger score \( \lambda_v \). Hence, we deploy the backup instance for type \( f \) in the server \( v^* \) with the maximal score \( \lambda_{v^*} \) (lines 9-11), i.e., \( f_{v^*} = 1 \). If no such server exists, we proceed to the next function type \( f \) (line 7).

Next, recall that a backup instance can support at most \( K \) primary instances. We should further associate the backup instance in \( v^* \) with \( K \) primary instances. To this end, we exploit the same design intuition to identify the primary instances that produce most piggybackable traffic. In particular, we sort primary function instances \( n \in \mathcal{N}_f \) in descending order of their contributions \( \lambda_{v^*,n} \) (line 13) and select the instances with the top-\( K \) scores \( \lambda_{v^*,n} \), denoted by \( n_1, n_2, \ldots, n_K \), to associate with the backup instance installed in server \( v^* \), i.e., \( J_{n_k,v^*} = 1, k = 1, 2, \ldots, K \) (lines 14-15). The above deployment and association procedure repeats until every primary instance has been associated with a piggyback backup instance or all the servers available for piggybacking have been fully occupied.

### 4.2 Piggybacking Chain Selection

Once piggybackable backup instances have been deployed, there may be several chains that can help piggyback the update information since each packet of any service chain traversing from a primary instance to a backup instance can help piggyback the update. That is, there is no need to select a dedicated chain to piggyback the updates. Instead, any chain with packets traversing through the backup instance can help forward the updates. This design is especially practical for a real network where service chains may join and leave dynamically. An intuitive strategy is piggybacking the periodical update information in a packet of any chain, i.e., first-come-first-serve (FCFS). However, different chains usually go through different function instances and, thereby, traverse through various path lengths. To save the traffic load for the entire network, a more reasonable strategy is to ask the shortest chain to help piggyback periodical updates. This alternative, however, faces another issue: the traffic arrival rate of the shortest chain may not be high enough to deliver periodical updates on-time. As different chains typically generate heterogeneous traffic rates along paths of different lengths, we aim at selecting piggybacking chains with consideration of both the update interval and the update cost.

As packet arrivals of a chain are usually unpredictable, we propose a bounded-waiting chain selection scheme. In particular, we partition time into epochs, each of which has a fixed interval \( T \) equal to the update interval. At a high level, in the beginning of epoch \( i \), each primary function instance predicts whether a chain would arrive in epoch \( i \) and identifies the chain with the shortest path to its backup instance as the candidate \( c^* \) from those who are likely to arrive in epoch \( i \). The primary instance then waits for the packet of the candidate \( c^* \) for piggybacking the update. If \( c^* \) indeed arrives in epoch \( i \), the information can be smoothly piggybacked to the backup instance. If not, the primary instance will embed the update in the first packet of any chain in epoch \( i + 1 \), i.e., FCFS. If, unfortunately, there is no packet arrival in an epoch, a primary function can send a stand-alone update to its backup instance. By doing this, we bound the waiting time within the epoch interval \( T \) and hence balance the tradeoff between the update cost and the update latency.

To estimate the arrival pattern of a chain, we assume that packet arrivals of a chain follow a Poisson process, i.e., the inter-packet time following the exponential distribution with mean \( 1/\lambda \), where \( \lambda \) is the mean traffic arrival rate and can be measured from historical packets. Hence, the primary instance can predict the arrival time of a chain based on the arrival time of its previous packet and the mean inter-packet time. Note that even if the packet arrival pattern does not follow the Poisson process, we can still measure the empirical mean packet arrival rate via packet sampling and INT technologies. With the prediction of traffic arrival patterns, the primary instance can collect the chains whose next packet would arrive in epoch \( i \) and find its candidate \( c^* \) in the beginning of epoch \( i \). Fig. 2 illustrates an example of our bounded-waiting chain selection scheme. In epoch \( i \), the primary function predicts that chains \( c_2, c_3, c_5, \) and \( c_6 \) may have packet arrivals and selects \( c_5 \) (with the shortest piggyback length) as its candidate. It then waits for \( c_5 \)’s arrival in epoch \( i \). However, chain \( c_5 \) in fact, does not arrive in epoch \( i \) as expected. Then, the primary instance embeds the update information in the first packet of epoch \( i + 1 \) (i.e., chain \( c_3 \)). It again performs the same prediction and selects \( c_3 \) as the candidate in the beginning of epoch \( i + 1 \). This time, \( c_3 \) arrives in epoch \( i + 1 \) as expected. Therefore, the
primary instance can ask $c_4$ to piggyback the next update information.

### 4.3 Stand-Alone Instance Deployment

After piggyback-mode deployment, some primary instances, denoted by $\mathcal{N}_{\text{alone}}$, may not be able to find any chain traversing from it to any server available for backup. To cover those remaining primary instances, we will deploy their backup instances in the available servers and send the updates using stand-alone packets. Note that an existing backup instance deployed in the piggyback mode may still be available if it serves fewer than $K$ primary instances. That is, those backup instances can be reused by stand-alone primary instances. For a function type $f$, the set of its available servers can be defined as

$$\mathcal{V}_f = \{v : \sum_{f' \in \mathcal{F}} I_{f', v} < B_v \| (I_{f, v} \& \sum_{n \in \mathcal{N}_f} J_{n, v} < K)\}. \quad (4)$$

An intuitive deployment is to place a backup instance as close to its serving primary instance as possible. However, the problem is not that simple since 1) a backup instance is usually shared by several primary instances, and 2) multiple primary instances compete for limited server resources. Consider Fig. 3 as an example. Assume that servers 1, 3, 4, and 6 can only install one backup instance. If primary instances NFs G and F in server 3 and server 4, respectively, both configure their backup instances to the closest available servers, i.e., server 4 and server 3, they will run out of the resources nearby the last primary instance, NF E in server 6. Then, the only available remaining server, server 1, will be very far from the last primary instance NF E, leading to a large update cost for NF E. However, if NF F in server 3 can backup in server 1, NF E in server 6 should be able to backup in server 4 to reduce the overall update cost.

To resolve this issue, the remaining primary instances should cooperate with each other and identify their backup instance positions to minimize the overall update cost. Algorithm 2 summarizes our cooperative stand-alone instance deployment scheme. Intuitively, a primary instance close to more available servers has more options and, hence, should make its decision later. On the contrary, a primary instance only close to a few available servers should get a higher priority to install its backup instance.

To realize this idea, we quantify the priority of each remaining primary instance $n \in \mathcal{N}_{\text{alone}}$ by the additional update cost $\Delta_n$, which is defined as the difference between its shortest path length and its second shortest path length to any available server in $\mathcal{V}_{f(n)}$ (line 3). For example, if the lengths of the shortest path and the second shortest path are $k$ and $k'$, respectively, the additional update cost $\Delta_n$ will be $(k' - k) \times K$ for an update packet of $L$ bits. Specifically, a primary instance with a smaller additional update cost will be assigned a lower priority since its update cost can still be low even if its backup instance locates in the second closest server. Hence, we sort the primary instances in $\mathcal{N}_{\text{alone}}$ in descending order of their $\Delta_n$ (lines 4-6) and sequentially associate them with their closest available server $v^*$ in order (lines 9-10). If there has existed a non-overloaded backup instance in $v^*$, it can directly be reused by the associated primary instance. Otherwise, we deploy a new backup instance in $v^*$ to serve the associated primary instance (line 8). The server $v^*$ will be removed from the available set $\mathcal{V}_f$ if it has been fully occupied after an assignment. The above procedure repeats until all the primary instances have been associated with a backup instance or none of the servers is available (lines 2, 7).

### 5 Performance Evaluation

We conduct extensive simulations written in C to evaluate the performance of PiggyBackup in a fat tree topology [31], which has been widely used in many data center networks. We deploy a 4-pods fat tree, which consists of 16 hosts and three layers of switches, i.e., 8 edge switches, 8 aggregation switches and 4 core switches. Each switch connects to a physical machine, which installs a number of VMs. Without otherwise stated, the default number of function types and chains are set to 20 and 50, respectively,
We generate a set of chains, each of which is from a random originating host to a random destination host and requests a sequence of NFs randomly selected from a set of function types \( \mathcal{F} \). The length of a chain is also picked randomly, varying from 1 to 20. We leverage a simple closest instance assignment scheme to assign primary instances to a chain. That is, for a chain requesting NF \( f_i \rightarrow f_{i+1} \) in steps \( i \) and \( i+1 \), the instance of \( f_i \) will forward this chain to the closest instance of \( f_{i+1} \). The traffic arrival pattern of each chain follows a Poisson process with the mean arrival rate of 1 packet per millisecond. Since our goal is to demonstrate the benefit of reusing SFCs, the primary instance assignment for SFCs should not affect the performance much.

We compare PiggyBackup with two baseline algorithms: i) random placement, which deploys backup instances in randomly selected servers without considering the locations of primary instances, and ii) shortest path based placement: primary instances sequentially pick the closest available servers to deploy (or reuse) their backup instances, while the selection order of primary instances is determined randomly. Our evaluation will examine the impact of number of chains, the impact of server capacity, the impact of backup-primary association limit, the effectiveness of chain selection, and the performance of stand-alone backup instance placement.

### 5.1 Impact of Number of Chains

We first check the percentage of primary instances whose backup can be piggybacked in the three comparison schemes. Fig. 4(a) shows the results when the number of chains varies from 10 to 50. The figure shows that, as the number of chains increases, the opportunities of piggybacking grow accordingly, matching the intuition of our design. Since our design explicitly considers the locations of primary instances and the traversing paths of chains, we can fully utilize the piggybacking opportunities and obtain almost 100% of piggybackable instances. However, random placement and shortest path based deployment would underutilize the opportunities as they do not consider the routing of chains.

Fig. 4(b) demonstrates the piggybacking hop counts of the comparison methods. The results show that random placement does not consider the locations of primary instances and, thus, lead to long piggybacking paths. Shortest path based placement achieves the minimal piggybacking hop counts since it always deploys the backup instances nearby the primary instances. However, as shown in Fig. 4(a), it supports piggybacking for only 40%–60% of primary instances. Hence, those non-piggybackable instances still need to use stand-alone packets to deliver updates, as a result increasing the overall cost. By contrast, PiggyBackup allows almost all the primary instances to piggyback their updates, through a slightly longer path.

We then plot in Fig. 4(c) the total number of update bytes, including piggybacking and stand-alone packets, of the three methods for every update event. The results verify that shortest path based placement sends stand-alone updates for a large proportion of primary instances and, overall, produces a significantly higher update overhead. Though our piggybacking updates traverse through slightly longer paths, the average overall overhead can still be reduced by 39.56%, as compared to shortest path based placement, since
we fully utilize piggybacking opportunities and minimize the stand-alone update cost. While the total size of every update event is only a few KBs, the overhead saving can be significant when there are many functions coexisting in the network and updating frequently at the same time.

5.2 Impact of Server Capacity

In this simulation, we examine the impact of backup capacity of each server. Figs. 5(a,b,c) illustrate the percentage of piggybackable instances as the network includes 10, 20, and 30 chains, respectively. For each figure, we plot the results when the backup capacity varies from 2 to 6. The results show that, when the backup capacity increases, the piggybacking opportunities grow accordingly. The percentage converges when the backup capacity increases to 4, showing that a finite backup capacity can already ensure full piggybacking updates. When the backup capacity is large enough, the performance of various numbers of chains becomes indifferent. This explains that, when a system supports sufficient backup capacity, even a small number of chains can already realize the benefits of piggybacking.

Fig. 6 summarizes the piggybacking percentage for various numbers of chains and backup capacity. The primary capacity of each server is fixed to 8. The figure shows a similar trend, in which the piggybacking opportunities can be mostly utilized when the backup capacity grows above 3, regardless off the number of chains in the network. Even if each server can only install two backup instances, PiggyBackup can still allow more than 93% of instances to piggyback their updates. We next fix the total capacity of each server, but change the ratio of resources allocated to primary and backup instances. For example, a 3:1 ratio implies that, in a server, 75% of instances are primary instances, while 25% are backup instances. Fig. 7 shows the percentage of piggybackable instances as the primary capacity varies from 8 to 16. The results demonstrate that the piggybacking opportunities are closely related to how much percentage of server resources is used for backup. If servers reserve fewer resources for backup, the piggybacking opportunities degrade. Resource allocation for primary and backup instance deployment is an interesting issue worth future studies.

5.3 Impact of Backup-Primary Association Limit

We then check how the performance changes with the value of $K$ (maximal number of primary instances that can be associated with a backup instance). We try two different configurations. In Fig. 8, we fix the ratio of primary capacity to backup capacity per server to 2:1, while in Fig. 9, we
fix the back capacity to 3 but vary the primary capacity from 6 to 14. Recall that a smaller $K$ means that each backup instance can only serve fewer primary instances. That is, the degree of competition among primary instances becomes more severe when the system is short of backup instances. The figures confirm again that the piggybacking opportunities decrease as $K$ gets smaller.

Fig. 8 shows that, when the overall capacity per server is small, e.g., 6 primary instances per server, only a few backup instances are deployed and the piggybacking opportunities become small since fewer chains can traverse through a limited number of backup instances. Similarly, given a fixed number of backup instances, as in Fig. 9, an increasing number of primary instances leads to more severe competition, as a result making some primary instances not be able to find any piggybackable chains. The results reveal that piggybacking opportunities not only depend on the number of chains but also the number of back instances distributed in the network.

### 5.4 Effectiveness of Chain Selection

We next check whether our chain selection design can effectively reduce the piggybacking cost as the mean packet arrival rate is configured to 1 and 2 packets per millisecond, respectively. We also compare our chain selection with naïve FCFS. The results illustrated in Fig. 10 show that FCFS introduces a much higher piggybacking hop count since primary functions are more likely to piggyback the update states in a chain traversing along a long path. With our arrival prediction, we try to embed the updates in shorter chains if possible, as a result reducing the hop count by around 27.5% and 39.35% with respect to the packet arrival rate of 1 and 2 packets per millisecond, respectively. The figure also shows that a higher traffic rate increases the probability of identifying a short piggybacking chain and results in a smaller piggybacking cost.

We further plot the success probability of chain selection in Fig. 11 when the packet arrival rate is configured to 1 and 2 packets per millisecond, respectively. The success probability here means the number of epochs whose candidate identified by our chain selection actually arrives in that epoch divided by the total number of epoches. For example, if our candidate selection in 80 out of 100 epoches can actually arrive in the epoch and help piggyback the update, we say that the success probability equals 80%. The results show that, when the packet arrival rate is sufficiently high (2 packets per ms), over 80% of our prediction can correctly identify the arrival events of the candidate chains, as a result helping piggyback the update through a shorter path and reducing the forwarding latency effectively. Even for a lower arrival rate (1 packet per ms), we can still identify the candidates with a probability of around 60%–70%. The lower probability is due to the few arrival events. Overall, we can conclude that, with arrival prediction, each primary function can have a fairly high opportunity to piggyback the update information in the identified shorter chain candidate and, thus, reduce the update cost.

### 5.5 Impact of Network Density

We next check the impact of network topology on the update costs. In this simulation, we deploy 20 servers but
connect any two servers with a random probability, following the uniform distribution. To tune the density of a network, we set the mean connection probability to 20% and 80% to simulate a sparse and dense network, respectively. Figs. 12(a), 12(b) and 12(c) illustrate the ratio of piggybackable instances, the total hop counts of piggybacking and the total update costs, respectively, of the two different topologies. Fig. 12(a) shows that the piggyback ratio of a sparse graph is higher than that in a dense graph. The reason is that, when a network is sparse, SFCs only have a few available paths and need to go through more network links, which hence increases the probability of traversing through multiple primary instances and backup instances. This can also be observed in Fig. 12(b), which illustrates that the piggybacking path in a sparse graph is far longer than that in a dense graph. Finally, Fig. 12(c) indicates that, though a dense graph has fewer piggybacking opportunities, it has more links and usually results in a shorter piggybacking path. Hence, the overall update cost of PiggyBackup in a dense graph is much lower than that in a sparse graph.

5.6 Performance of Stand-Alone Backup

Finally, Fig. 13 compares the backup hop count of PiggyBackup’s cooperative stand-alone instance deployment and naive shortest path based deployment. The results show that the stand-alone cost increases as the number of primary instances per server increases due to a limited number of chains and, thus, limited piggybacking opportunities. By explicitly controlling the backup placement order of prioritized primary instances, we can better utilize the remaining available resources to reduce the cost of non-piggybackable primary instances, as compared to the simple shortest path based scheme. The gap between the two solutions grows as a network has more primary instances, which should compete for limited backup capacity. Recall the results shown in Fig. 4(c). The reduced overall update cost in terms of update bytes is also contributed by a more efficient cooperative stand-alone instance deployment scheme of PiggyBackup.

6 Conclusion and Future Work

In this paper, we presented a backup NF instance placement framework to provide fault tolerance and ensure state consistency for a software-defined network. Our design reuses existing service chains to piggyback information and, thereby, reduces network usage for periodic state updates. We have derived the joint backup deployment and assignment problem as an ILP model and proposed heuristic algorithms to enhance piggybacking opportunities and minimize the stand-alone update cost. A chain selection strategy was also developed to identify shorter chains for piggybacking subject to a constrained update latency. The simulation results show that the more SFCs available in a network, the higher gain PiggyBackup can achieve, verifying the benefits of piggybacking. Overall, PiggyBackup reduces the update traffic load by 39.56% and 47.65%, respectively, on average in a fat-tree topology as compared to shortest path based placement and random placement.

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